Linked Markets:
Innovation, the Dynamics of Industries
and General Purpose Technologies

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Deutsche Zusammenfassung

Im Rahmen dieser Dissertation wird gezeigt, dass Märkte, Industrien und Technologien mit verknüpften Erträgen sowie Upstream und Downstream Verbindungen, im Vergleich mit diesbezüglich als isoliert zu betrachtenden Märkten, Industrien und Technologien, einigen speziellen Dynamiken hinsichtlich der Wirtschaftsaktivitäten und Innovationstätigkeiten unterliegen.

Den Schwerpunkt der Promotionsschrift bilden Spezialfälle verknüpfter Mrkte, welche durch das Vorliegen von *General Purpose Technologies* (GPT, zu Deutsch: Allzweck–Technologien) geprägt werden. Bei GPTs handelt es sich um Technologien, die sich durch eine weitreichende Durchdringungsfähigkeit und Verbreitung, fortlaufende Weiterentwicklung und Verbesserung sowie das Hervorbringen von komplementären Innovationen in verbundenen Industrien, charakterisieren. GPTs stellen damit 'Sonderfälle' auf dem Gebiet des technologischen Wandels und der Innovationen dar und bilden, ob ihrer Besonderheiten, einen der Schwerpunkte dieser Dissertation.

Etwas abstrakter formuliert, können GPTs als Upstream Märkte, die mit einer Vielzahl von Downstream Anwendungen verbunden sind, betrachtet werden. Diese Eigenschaft macht sie zu einem zentralen Treiber ökonomischen und technologischen Wandels in verbundenen Märkten. Grund hierfür ist, dass die Verbindung zwischen GPTs, ihren Anwendungsgebieten und den betreffenden Industrien, Einfluss auf die Entwicklung und Verbreitung technologischen Wandels sowie die wirtschaftliche Leistungsfähigkeit hat. Aus diesem Grund ist Mehrzahl der Kapitel dieser Dissertation den Dynamiken, welche Industrien und Innovationen inhärent sind, vor dem Hintergrund des Einflusses von GPTs gewidmet.

Die Analyse im Rahmen dieser Dissertationsschrift reicht aber über die volkswirtschaftliche Betrachtung von Märkten, die durch GPTs und deren Anwendungsbereiche miteinander verknüpft sind, hinaus. In einigen Kapiteln werden die Untersuchungen auf Themen wie Marktselektion oder wirtschaftspolitische Intervention erweitert. Dabei stehen Sonderfälle, und weniger Gesetzmäigkeiten im Fokus. Verletzungen der Replikator–Dynamik — erkennbar durch regressive Entwicklungen bezüglich der Marktselektion und bestimmt durch Vorliegen von vertikalen Beziehungen — stellen ein Beispiel solcher Irregularitäten dar. Diese werden zunächst identifiziert und anschliessend in die Entwicklung einer allgemeingültigeren Theorie zum Wettbewerb, im Sinne von Marktselektion und –Neu–Allokation, einbezogen. Ebenfalls in diesem Zusammenhang werden verschiedene Politikmassnahmen, welche die Beschränkung von Verdrängungseffekten im Kontext der Kommerzialisierung wissenschaftlichen Wissens oder wissenschaftlicher Erkenntnisse zum Ziel haben, erörtert und einer experimentellen Untersuchung unterzogen.

Das zweite, dritte und vierte Kapitel widmen sich vollständig dem Themenkomplex der GPTs.

Erstgenanntes beinhaltet eine umfassende Literaturübersicht der Theorien zu GPTs, von welcher ausgehend, die mikroökonomischen sowie industriedynamischen Theorien als rahmengebend für die anschliessende Analyse bestimmt werden, um somit den konzeptionellen sowie definitorischen Schwierigkeiten bei der Bearbeitung des Feldes der GPTs entgegenzutreten. Die bedeutendsten theoretischen Bausteine für eine mikroökonomische Betrachtung von GPTs werden im Zuge dessen vorgestellt und diskutiert.

Kapitel Drei weitet die Analyse des vorhergehenden Kapitels durch eine Fokussierung auf aktuellere Beiträge zu GPTs aus, wobei mit der Konzeptualisierung von GPTs, als ein Spezialfall der Ökonomik verbundener Märkte, begonnen wird. Insbesondere soll in diesem Kapitel ermittelt werden, ob die bestehenden Theorien zu GPTs fundiert und erkenntnisbringend sind. Ein bezüglich solcher Fragen positives Ergebnis unterstützend, wird das Kapitel eine Verbindung zwischen GPTs, den Theorien zu Ausstrahlungs– und Übertragungseffekten von Wissen und Forschungs– und Entwicklungserkenntnissen sowie Entwicklungsdivergenzen begründen.

Beiden Verallgemeinerungen liegt die Betrachtung von GPTs als ein Netzwerkphänomen zugrunde, wobei der Forschungsschwerpunkt nicht auf einer Herausarbeitung eines alleinstehenden, bestimmten GPTs sondern vielmehr auf der Analyse der Vielzahl verschiedener Impulse und Effekte, hervorgerufen durch das Entstehen eines GPTs, liegen wird.

Der letzte Abschnitt des Kapitels widmet sich der empirischen Untersuchung von GPTs. Hierbei ist vorgesehen, dass die erarbeiteten Generalisierungen als Leitfaden zur Gestaltung von empirischen Untersuchungen von Sonderfällen, wie sie beispielsweise in Form von GPTs auftreten und die nicht auf Fallstudien oder Patentanalysen begrenzt sind, fungieren. In diesem Zusammenhang wird ein nichtparametrischer Vergleich der variierenden Verteilungen industrieübergreifender F&E–Wachstumsraten mit dem Ziel, beschleunigte Innovationstätigkeit als Folge von eines entstehenden GPTs nachzuweisen, vorgestellt.

Im vierten Kapitel soll sich der zugehörigen Frage gewidmet werden, wie GPTs entstehen — präziser formuliert, wie eine Technologie das namensgebende 'General–Purpose–Charakteristikum' ('Allzweck–Charakteristikum') erlangt. Eine erste und vorläufige Antwort auf diese Frage leitet sich aus einem analytischen Modell, welches den Wettbewerb zwischen den Upstream–Technologien bezüglich der Downstream–Märkte abbildet, ab.

Mithilfe des Modells wird zunächst eine statische Beschreibung der möglichen Zustände, die sich aus technologischem Upstream Wettbewerb um Downstream Märkte ergeben können, vorgenommen: Die neue Upstream Technologie kann erfolgreich im Sinne einer vollständigen Marktbeherrschung sein, kann scheitern und nachhaltig randständig bestehen oder zusammen mit dem bestehenden GPT in annähernd paritätischer Art und Weise auf dem Downstream Markt koexistieren. Eine Erörterung wirtschaftspolitischer Massnahmen wird dem nachgestellt. In diesem Kapitel wird zudem ein erster Entwurf des dynamischen Modells präsentiert, in dem Netzwerkeffekte bezüglich der Technologie–Adoption auf Downstream Ebene in das Modell einbezogen werden. Dies gelingt über den Grad der Anschaffung, repräsentiert durch die Grösse Downstream–Nutzerbasis, sowie die Verteilung der relativen Leistungsfähigkeit der neuen Upstream–Technologie über die Downstream Industrien hinweg. Die Untersuchung der Einflussgrössen, welche die Verbreitung der Upstream–Technologien determinieren, soll die Wirkmechanismen und Prozesse, die zur Etablierung potentieller GPTs in den verbundenen Märkten führen, deutlich machen.

Die Kapitel Fünf und Sechs behandeln das Themenfeld der verbundenen Märkte aus verschiedenen Blickwinkeln. Ersteres führt das Konzept der Marktselektion dahingehend fort, als dass nun Märkte, die vertikal innerhalb der Wertschöpfungskette integriert sind, untersucht werden. Der Analyserahmen der Replikator–Dynamiken wird erweitert, indem die Möglichkeit, dass das Wirkprinzip des 'Überlebens des Stärkeren', im Kontext des Schumpeterschen Wettbewerbs, durch Verknüpfungen zwischen Upstream und -Downstream Märkten, ausgeschaltet oder sogar invertiert werden kann, einbezogen wird. Die erweiterten Replikator–Dynamiken, einschliesslich der Wertschöpfungsketten, werden modelliert und unter verschiedenen Szenarien — unterschiedliche Ausprägungen der Wertschöpfungskette ('*Ordered Matching*' oder '*Random Matching*'), dynamischen Innovationsrenditen sowie Umstellungskosten — computergestützt simuliert. Kernaussage des Kapitels ist damit, dass verknüpfte Wertschöpfungsketten, Verletzungen der Replikator–Dynamik und damit rückläufige Entwicklungen bezüglich der Marktselektion induzieren knnen.

Es wird gezeigt, dass Marktselektion innerhalb der Wertschöpfungskette im *Random Matching*–Szenario, welches die Möglichkeit des Handelspartnerwechsels bietet, bei jedem Innovations– und Skalenertrags–Setting zu einer anfänglichen Phase mit hoher Volatilität bezüglich der Marktanteile führt. Damit wird einer neuartiger Beitrag zum Verständnis von Marktturbulenzen und deren Persistenz über Industrielebenszyklen und technologische Rahmen hinweg, geleistet.

Die Möglichkeit des Partnerwechsels, verbunden mit verschiedenen Formen der damit einhergehenden Umstellungskosten, beschleunigt die Veränderungen der gesamtwirtschaftlichen Leistungsfähigkeit und beeinflusst die Selektionsdynamiken, wobei die Intensität dieses Einflusses variiert. Marktselektion ist auf den verschiedenen Stufen der Wertschöpfungskette unterschiedlich intensiv ausgeprägt, wobei die stärksten Effekte an den End–

Stufen der Wertschöpfungsreihe auftreten. Diese Erkenntnis schafft die Möglichkeit der Gestaltung einer Wettbewerbspolitik die sich an einer mit dem Schumpeter'schen Wettbewerb vergleichbaren, Marktheterogenität orientiert.

Im anschliessenden sechsten Kapitel steht ein noch speziellerer Fall der verbundenen Märkte im Fokus. In diesem wird das Konzept des Marktes deutlich weiter gefasst und zwar als '*domain*' (Domäne oder Geltungsbereich). Dem folgend wird nun der akademische Bereich mitberücksichtigt, und mit den sich aus dessen Leistungen ergebenden, Anwendungs– und Kommerzialisierungsbereichen anhand der Gründung von Spinoff–Unternehmen verknüpft. Dieser Abschnitt liefert eine experimentelle Untersuchung von wirtschaftspolitischen Eingriffen, welche auf die Verbesserung des Wissenstransfers sowie der Investitionen von dem Universitäts– und Hochschulbereich in die akademischen Spinoffs, abzielen.

Der Schwerpunkt der Analyse liegt auf der Herausarbeitung der Wirkungen verschiedener wirtschaftspolitischer Massnahmen, einschliesslich der langfristigen Effekte die daraus resultieren. Zu diesem Zweck wird ein Modell erarbeitet und Hypothesen abgeleitet, welche anschliessend anhand von, im Experimentallabor ermittelten, Reaktionen verschiedener Versuchspersonen überprüft werden. Als Hauptergebnis der Studie kann dabei festgehalten werden, dass monetäre Anreizsysteme (Subventionen) die Höhe der Investition nicht signifikant steigern, während Massnahmen bei denen Behörden zu dem gewünschten Verhalten anregen, die Investitionen für die Dauer des Eingriffs erhöhen, und keine langfristigen (Post–Interventions–Effekte) nachteiligen Folgen aufweisen. Die hieraus abgeleitete Implikation könnte dergestalt formuliert werden, dass ein deutlicherer Fokus auf Kommunikations–Politik gelegt werden sollte. Diese Massnahmen könnten ein deutlich wirtschaftlicheres und gleichzeitig langfristig nicht nachteiliges, Werkzeug darstellen, mit welchem die Verbindung von Wissenschaft und Industrie weiter forciert werden könnte.

Zusammengefasst kann festgehalten werden, dass mit dieser Dissertation ein nennenswerter Beitrag zu dem, sich im Aufkommenden befindlichen Forschungsgebiet der verbundenen Märkte geleistet wird. Die Untersuchung der Dynamiken von Märkten und Technologien unter Einbeziehung verschiedener Aspekte wie dem Einfluss von GPTs, Innovation und Selektion in Wertschöpfungsketten sowie der Möglichkeit, dass wirtschaftspolitische Eingriffe den Weg fr eine Kommerzialisierung des Wissens heraus aus dem akademischen Bereich in den Markt ebnen, ermglicht eine komplexere und ganzheitlichere Betrachtung volkswirtschaftlicher Dynamiken.

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Chapter 1

Introduction

"*Put on Schumpeterian eyeglasses, (...) and look around you! You will find many examples of structural tensions and of development blocks extending over wide areas of the economic and social life.*"

— Erik Dahmén

"*History never repeats itself, but it often rhymes.*"

— Attributed to Mark Twain

1.1 From General Purpose Technologies to Linked Markets

Finding regularities is the 'bread and butter' of science,[1] and the 'dismal science' is no exception. The identification of statistical regularities in the evolution of industries (Dosi, 2007) is the rationale behind a non–negligible share of research in the field of Economics of Innovation, Evolutionary Economics, and Industrial Dynamics. The reproduction of stylized facts (Kaldor, 1957) is at the core of many modeling and empirical exercises in

[1] Paulson, S. (2013), *Monsters, Marvels, and the Birth of Science*, Nautilus, Issue 004.

Macro–, Meso– and Microeconomics. This Thesis is instead interested in what deviates from stylized patterns — it is a study of irregularities.

In the Economics of Technological Change — depending on the degree of approximation and the particular lenses of analysis scholars wear — irregularities are called radical innovations, disruptive innovations, drastic innovations, breakthroughs, macroinventions, 'inventions of methods of inventing', *dominant filières*. The common characteristic of all the definitions in this still incomplete list is the degree of qualitative difference between such technologies and those that are incremental or less game–changing. However, technologies are systems in nature; they are composed of parts that are systems themselves, in a recursive way, and this feature makes less trivial the identification of irregularities in the technology domain. Depending on how fine–grained the level of analysis is, a radical technology can be seen as incremental, and vice versa. For example, from the viewpoint of the main functions delivered, a present–day automobile has been subject only to incremental changes compared to the original innovation introduced by Daimler and Benz at the end of the Nineteen Century. In both periods, in fact, an automobile mainly delivers the service of mobility. However, the complexity of cars abruptly increased over the years, and an automobile nowadays is a complex system of interrelated parts that rely on informational and electronic platforms rather than mechanical ones. From this perspective, what looked at a first glance as a sequence of incremental innovations appears now as a radical change.

Given the complex nature of technologies, to assess the radicality of technology is a rather non–simple goal. However, technologies that can be classified as irregularities display another characteristic that is more relevant than any degree of ambiguous 'radicality'. They show *generality of purpose*. With the expression generality of purpose we indicate the feature of a technology suitable to be used as a component, or input, by many and often unrelated other technologies and economic activities. Hence, generality of purpose is a measure of the *pervasiveness* of a certain technology. The electric dynamo, information and communication technologies, the laser, and few other technologies display a significative generality of purpose, that makes them 'unique' and belonging to an *ad hoc* category within the broad set of technological innovations. The literature labels these technologies 'General Purpose Technologies' (hereinafter GPTs) and defines them as technologies characterized by pervasiveness, continuous improvement, and inducement of innovational complementarities in linked industries (Bresnahan and Trajtenberg, 1995; Bresnahan, 2010; Lipsey et al., 2005). GPTs are the irregularities of the world of technological change and innovations and, given their peculiarity, they are inter alia the *fil rouge* of this Thesis.

In the history of science, and especially during the 'great age of wonders' preceding the advent of modern science (Daston and Park, 1998), irregularities have been usually collected and stored in *Wunderkammern*, or 'Cabinets of Curiosity'. This Dissertation is not meant to be a Cabinet of Curiosity listing and classifying GPTs. Instead, it is a study into their nature and the conditions that allow them to become pervasive. One of the main claims of the Thesis is that the irregularities of the world of technological change are not unique starting from their very 'birth'. Generality of purpose is a feature that can be 'cultivated' and it is better represented by a process leading to pervasiveness rather than as a characteristic assumed a priori. Economic theory usually disregards or assumes the degree of pervasiveness of technologies, and this limits scholars' understanding of the profound role played by technological change in the economy. In fact, according to Wright,

> (. . .) the importance of many of the great innovations of the past century (. . .) was woefully underestimated even by the inventors, because they could not foresee the extent of future improvements in the technology, because the scope for application depended on the unforeseen development of complementary technologies elsewhere in the economy, and because future uses emerged as parts of a complex interdependent system that no one could have predicted in advance. (Wright, 1997, pp. 1561–1562)

The same uncertainty characterizing the assessment of the relevance of technologies can also be sensed from the words of some direct protagonists of technological changes. For example, Rosenberg cites Charles Townes recalling how the first reaction to the invention of the laser happened to definitely underestimated its potential:

> Bell's patent department at first refused to patent our amplifier or oscillator for optical frequencies because, it was explained, optical waves had never been of any importance to communications and hence the invention had little bearing on Bell System interests. (Rosenberg, 1998)

Despite the uncertainty that characterizes technological change in general and the establishment of GPTs in particular, understanding this dimension of change if of utmost importance. In fact, it will help scholars to build a bridge between the short–run mechanisms and the long–run trajectories of innovation and economic growth. Until now, Microeconomics of innovation, Industrial Dynamics, and theories of Long Waves have followed close but rarely intersecting paths. A new view of GPTs as the one outlined in this Thesis may mark not the beginning of the end, but the end of the beginning of this research avenue (Lipsey et al., 2005).

It has to be pointed out that this is not a Thesis on merely 'important' technologies. Importance, measured using the intensity of some outcome variables — for example, the value of patents' licensing fees, stock market values, and citations — can overlap but does not coincide with pervasiveness. Economically important technologies are often not pervasive. In fact, the peculiar externalities produced by GPTs cannot be well captured by standard measures (Carlaw and Lipsey, 2002), given that their effect is intangible in nature and has to do with opening up new opportunities and offering new logics for the recombination of existing inputs and technologies. In a nutshell, irregularities are so because they are *enabling*, rather than important.

For economists, to grasp the dynamic processes leading to the establishment of enabling GPTs means to adopt a different viewpoint on this kind of technological change, one that conceives breakthrough irregularities as the result of multiple determinants and interactions. Such a viewpoint has to be grounded in the meso and micro dimensions, meaning those focusing on firms and industries as the unit of analysis. As soon as GPTs are considered as pervasive technologies *in the making*, the focus of research has to switch from the very 'singleton technology' (Mokyr, 2005) to the linkages between the industries and markets that favour or hinder technological diffusion across diverse economic activities. In this sense, a study of irregularities such as GPTs becomes a contribution to a more general *Microeconomics of heterogeneous technological change*. Irregularities are the result of the restless stream of (positive and negative) feedbacks occurring in economic and technological domains. In order to provide not the proximate description of yet another Cabinet of Curiosities, but the identification of the ultimate generating processes driving economic and technological evolution, the analysis has, therefore, to focus on feedbacks and their transmission channels. Hence, to understand irregularities it is necessary — although not sufficient — to look at the edges, namely at the linkages between our objects of interest.

Following this line of though, the focus of the Thesis evolves into the analysis of *Linked Markets*, where with 'linked' we stress the importance of connectivity, and with 'markets' we go beyond the narrow technological dimension in order to widen the framework of study. In a nutshell, the Thesis posits that *markets, industries, and technologies displaying linked payoffs and connections upstream and downstream are subject to peculiar dynamics for what concerns economic and innovative activities compared to markets, industries, and technologies considered in isolation*. GPTs dynamics thus become a particular case of linked markets. In a stylized way, those producing GPTs can be considered as upstream markets connected with a large set of downstream applications. This character places them as one of the core engines of economic and technological transformation in linked markets, as the linkage between GPTs, application sectors and industries affects the incentives for technological innovation and diffusion as well as economic performances. Therefore, most of the Chapters in the Thesis study the dynamics of industries and innovation in the presence of GPTs. Furthermore, the Thesis goes beyond the enquiry of markets where the linked objects of analysis are GPTs and application industries. Some Chapters extend the analysis of linked markets to topics such as market selection and policy. Also in these cases, the accent is posed on irregularities rather than on regularities. For example, the violations of the replicator dynamics — regressive developments of market selection — determined by the existence of vertical relations are identified and used to develop a more general theory of competition for the market, selection and reallocation. On the same vein, the constellation of public policy measures that limit or contrast crowding out in the context of commercialization of academic knowledge is highlighted and tested using experimental methods.

Having presented the rationale behind the choice of linked markets and GPTs as the focus for this study, the next Section describes in details the structure of the Thesis.

1.2 Structure of the Thesis

The general aim of the Thesis is to offer new theoretical insights on how linked markets affect technology and economic dynamics. The Thesis is structured around five Chapters. Chapters 2, 3 and 4 address the topic of linked markets focusing on GPTs. Chapter 5 and Chapter 6 deal with linked markets from other perspectives, namely those of market selection and public policy interventions to foster academic knowledge commercialization.

The author developed the Chapters of the Thesis benefiting from the human and scientific atmosphere of the Research Training Group 'The Economics of Innovative Change', jointly organized by the Friedrich Schiller University Jena and the Max Planck Institute of Economics and supported by the German Science Foundation. After two years of doctoral studies as scholarship holder, the author has been employed at the Chair of Prof. Dr. Cantner at the Friedrich Schiller University Jena, where grew up professionally and gained even more from the fruitful and inspiring interactions with colleagues. The author presented the results of his research in a number of internal seminars (the Jena Economic Research Workshops and the Jena Summer Academies on Innovation and Uncertainty), invited seminars (at University of Insubria, Varese and at Sant'Anna School of Advanced Studies, Pisa) and international conferences, among which (in chronological order) the DIMETIC Summer School in Maastricht, the DRUID Conference 2013 in Barcelona, the 25th EAEPE Annual Conference in Paris, the 1st Doctoral Workshop in Economics of Innovation, Complexity and Knowledge in Turin, the Workshop Explaining Economic Change in Rome, the EMAEE Conference 2015 in Maastricht and the DRUID Conference 2015 in Rome.

1.2.1 Chapter 2

Chapter 2 of the Thesis, titled 'A New View of General Purpose Technologies', is a critical review of the received GPT–based theories. It suggests to ground the study of GPTs on the framework of Microeconomics of Innovation and Industrial Dynamics. The rationale behind the position defended in the Chapter is that this alternative route for theoretical analysis may offer a solution to the conceptual and definitional problems characterizing the literature on GPTs. The title of the Chapter is inspired by the classic contribution of Atkinson and Stiglitz (1969) on 'a new view of technological change': as technological change for Atkison and Stiglitz is localized and subject to various degrees of spillovers and learning, the modeling of GPTs in this Thesis has to be confronted with the micro– and mesoeconomic nature of industries' interactions that may lead a specific technology to become general purpose.

The Chapter starts positioning the study of GPTs within the relevant research trajectories, from Long Wave theories to Neo–Schumpeterian approaches down to New and Endogenous Growth Theory. Introduced as a useful concept to explain from a neoclassical viewpoint 'whole technological eras' (Bresnahan and Trajtenberg, 1995), GPTs turned to be as widely applicable as the technologies the concept wants to describe. The review of the models — mainly growth models — featuring GPTs suggests that while the existing analytical exercises shed light on the mechanisms leading to technology–driven fluctuations, they do not solve the identification problems related to the concept of GPT. The Chapter suggests, therefore, a first exploration of a Microeconomics of GPTs, assessing the usefulness of some theoretical categories used in Economics of Innovation and Industrial Dynamics to contribute to the understanding of GPTs. The concepts of network effects and dynamic returns to scale, dominant design and industry life cycles, collective invention and cooperation among inventors are expounded and linked to the core definitional criteria of GPTs.

The Chapter is co–authored with Uwe Cantner. The contribution share of the author is at least 50 percent. A version of the Chapter is published in Wagner and Heilemann (2012).

1.2.2 Chapter 3

Chapter 3, titled 'Generalizing General Purpose Technologies' builds on the issues raised in the previous Chapter to further improve our theoretical understanding of GPTs. It assesses the question whether the GPT–framework is still valid and useful despite the growing criticism towards the concept and its analytical and empirical applications. To support a positive answer to the question, the Chapter extends the conceptualization of GPTs by showing how the dynamics described by GPT models can be framed as special, but clearly identifiable, cases of related theories. The Chapter overviews recent contributions featuring GPTs and suggests to adopt the concept of GPT cluster (as defined in Bresnahan and Yin (2010)) as the relevant unit of analysis. Further, the Chapter offers two generalizations: the first relates GPTs and theories of spillovers, the second connects GPTs with theories of uneven development. Both generalizations go in the direction of interpreting GPTs as *network phenomena*. Accordingly, it is suggested that the focus of GPT–related studies should not lie in the identification of the single, precise GPT, but in the cascade of inducements and effects the establishment of a GPT generates.

For what concerns GPTs and spillovers, the Chapter highlights how GPTs generate a particular kind of externality that affect the returns of linked industries' innovative activities rather than economic outcomes. This peculiarity stems from the fact that GPTs are enabling technologies, meaning that they broaden the set of opportunities for technological exploration and recombination. For what regards GPTs and uneven development, the Chapter describes how the feedback process taking place within a GPT cluster may lead to a cascade of effects on the rest of the economy and how these effects, depending on the heterogeneous distribution of reactions to inducements in downstream industries, may result in synchronous or asynchronous changes.

The two aforementioned generalizations of GPTs are used to outline the first sketch of a theory of technological multipliers, where the focus is on the reverberation of enabling technological complementarities on related sectors' innovative activities. Contributions looking at similar phenomena, such as for example R&D multipliers, are described and connected with the proposed framework of analysis. A final Section of the Chapter deals with the empirical study of GPTs and suggests that the proposed generalizations can serve as a guideline to design empirical analysis of 'irregularities' such as GPTs that are not confined to case studies or patent analysis. A non–parametric exercise is provided; it compares over time the changing distributions of cross–industries R&D growth rates, meant to capture accelerations in innovative activities and, therefore, part of the effects produced by a GPT in the making. The proposed empirical approach responds to the need to develop, for economic dynamics, a 'theory of the growth rate', rather than simply a theory of growth (Metcalfe, 2003). The analysis offered in the Chapter is however limited to the domain of innovative activities.

Establishing a connection between the concept of GPT and the propagation of GPT–induced effects on innovative activities and the economy, the Chapter makes the case for considering GPTs a special case of interaction between linked technologies and industries. The focus has therefore been shifted towards the structure of connectivity between markets, and to the role it plays in shaping the chances for a given technology to gain prevalence and pervasiveness.

The Chapter is single–authored.

1.2.3 Chapter 4

Chapter 4, titled 'Competition for the (Downstream) Market: Modeling Acquired Purposes' completes the theoretical analysis started in Chapter 2 and Chapter 3 dealing with the question of how a GPT comes into being. We posit that the process through which a technology gains pervasiveness matters: the evolution of a technology can result in a broad diffusion or in a failure to spread. The literature on GPTs, with a few exceptions (Thoma, 2009; van Zon et al., 2003), assumes the generality of purpose feature of a given technology. However, the relevant phenomenon to be studied is what happens when generality is not assumed a priori. Therefore, the focus of the Chapter is on how purposes are 'acquired'. Purposes are meant in this

Chapter as ‘applications’, or uses.

The Chapter discusses how a study dealing with the process of purposes acquisition relates to the more general effort to understand the patterns of industrial connectivity that is receiving increasing attention in economic research. There are different reasons for such increasing attention to linked industries and linked markets, most considerably the application of network theorizing to several fields of economic theory (Carvalho, 2014; Carvalho and Voigtländer, 2014; Contreras and Fagiolo, 2014; Hausmann and Hidalgo, 2011; McNerney et al., 2013) and the re–discovery of input–output views of the economy to measure the effects of fiscal and industrial policies in the context of the current economic crisis (Foray, 2014; Hausmann and Rodrik, 2006; Stiglitz et al., 2013).

We introduce a simple model to describe the process leading a specific purpose technology to become a GPT. The model builds on the classic model of Bresnahan and Trajtenberg (1995) and introduces technological competition between an established GPT and one ‘entrant’ technology that strives to gain pervasiveness. The technological competition occurs in a setting featuring vertically–linked markets, where a continuum of downstream industries can adopt one of the possible alternative upstream input technologies. The competition among those technologies can result either in the establishment of a new pervasive GPT or in the persistence of the existing GPT as the dominant one. One of the main ideas introduced by the model is that downstream industries’ decisions, and therefore the (more or less) successful pattern of diffusion of an upstream new technology, depend on *comparative advantages*, rather than on absolute quality and cost of the GPT as in Bresnahan and Trajtenberg (1995). In this sense, the model is an adaptation of the ‘Ricardian’ (or assignment) model of international specialization of Dornbusch et al. (1977) in line with Cantner and Hanusch (1993), Acemoglu and Autor (2011), Cimoli (1988), Dosi and Soete (1983) and, more recently, Costinot (2009) and Costinot and Vogel (2015). In the version of the model proposed in the Chapter, the assignment/matching takes place between upstream technologies (industries) and downstream industries, rather than countries and products as in Cantner and Hanusch (1993) and skills/labor and tasks as in Acemoglu and Autor (2011). In a sense, the model can be considered as a model of competing technologies in line with Arthur (1989) that features industries' vertical relations, as well as an application of the Schumpeterian 'competition for the market' to a linked market settings.

The model provides in first stance a static description of the possible states that can be attained by the upstream technological competition for downstream markets: The new upstream technology can succeed in 'conquering' the whole downstream market, can fail and be confined in a niche, or can share the downstream market with the established GPT on a rather equal standing. Two scenarios — a *competition case* and a *niche case* — are discussed. The case featuring three upstream technologies competing for dominance and pervasiveness is provided as well. A discussion on policy interventions follows, indicating the possibility that 'policy mixes' intervening on different determinants and 'levers' can lead to a larger set of outcomes than usually considered. The Chapter develops also a first sketch of the dynamic version of the model, by taking into account the presence of network effects linking downstream adoption — so the 'purposes acquisition' captured by the size of the downstream user base — and the distribution of the relative performance of the new upstream technology across the downstream industries. The conditions for the existence of multiple equilibria are identified and related to the non–homogeneous response of the downstream continuum of industries to relative usefulness and costs changes.

The Chapter is co–authored with Uwe Cantner. The contribution share of the author is at least 50 percent.

1.2.4 Chapter 5

Chapter 4 establishes in the context of GPT–related models a first connection between competition and markets that are vertically linked. Chapter 5, titled 'Replicator Dynamics in Value Chains: Explaining Some Puzzles of Market Selection' pushes ahead this idea by asking if, by taking into account vertical relations — that is, value chains structures, one can explain same empirical puzzles characterizing the analysis of market selection.

Market selection and market reallocation are usually studied in the Neo–Schumpeterian framework of analysis using the replicator dynamics model (Metcalfe, 1994). The replicator dynamics models the competition for the market by showing how actors (firms, industries, regions) with a fitness above (below) the share–weighted average of that of the reference population will increase (decrease) their market share. The idea is to capture the Darwinian 'survival of the fittest' through a set of differential equations relating actors' market share rates of change to the period–by–period assessment of the above (below) average performance. Here, fitness is conceived as an indicator of 'goodness' and can be measured by unit costs, productivity, product quality, or any other performance measure.

The replicator dynamics is intuitively appealing but seems not to hold robustly when tested empirically. The limited empirical evidence of replicator dynamics at work questions the fact that market selection takes place at all. Alternatively, the theoretical predictions may not be verified due to an identification problem. Usually, in fact, the population boundaries of empirical data are those of industries. However, it is well known that industries aggregate heterogeneous activities, and such aggregation may cancel out any existing trace of market selection. A better definition of the context in which market selection takes place is therefore fundamental. Some contributions (Cantner et al., 2012) focus on specific markets rather than on industries, betting on their higher degree of coherence. In fact, signs of the replicator dynamics at work do appear in this type of analyses. An additional perspective is that suggested by this Chapter: the replicator dynamics may not show up in the data when firms are connected in value chains. The limited flexibility of value chains creates the chance for fit firms to be connected to less well–performing upstream and downstream partners. In this case, the survival of the fittest cannot be taken for granted, and violations of the replicator dynamics take place. We name these violations *regressive developments* and highlight their existence as a possible explanation for the empirical puzzles of market selection.

The Chapter provides an analytical study in which the extended replicator dynamics incorporating value chain relations is modeled and computationally simulated. Furthermore, innovation is introduced in the model according to three regimes of dynamics returns to scale: constant, increasing and decreasing returns. The effects of different innovation scenarios on selection are analysed comparing the cases of value chains ordered and random matching. In ordered matching, firms are linked in value chains according to their fitness ranking; this setting reproduces the standard replicator dynamics and only adds a many market layer structure to the working of the model. In random matching, firms are randomly connected, so that the situation in which fit and less fit firms are linked is likely to occur. In addition to that, we explore the possibility of partner switching across value chains, and analyze the resulting effect on performance under different switching costs regimes. For all the scenarios and regimes considered in the Chapter we run an exercise in an 'evolutionary accounting' (Dosi and Grazzi, 2006): we provide a decomposition analysis to disentangle how the change in firms costs — the chosen fitness — is determined by learning and innovation (the within effect), selection (the between effect) and the regimes of dynamics returns to scale (the covariance effect).

We develop five propositions summarizing the main results of the paper. In short, we find that firms being related into value chain structures and depending in their output capacity on their downstream partners do not necessarily increase their market share even though being most efficient. The very existence of value chains relations may induce violations of the replicator dynamics generating regressive developments of market selection. Furthermore, we show that market selection among value chains in the random matching scenario with the possibility to switch partners produces at the beginning a period of high market share volatility dynamics in any innovation and returns to scale setting, which provides a novel contribution to the understanding of market turbulence and its persistence along industries life cycles and technological regimes. Next, our results indicate that the possibility of partner switching, coupled with different 'regimes' of switching costs, hastens the change in aggregate fitness and affects with various intensities selection dynamics. Market selection affects with different magnitudes different value chain layers, with the strongest effect to be found at the final end of the value chain. Acknowledging that market selection 'bites' with different strength different markets linked in value chains open room for designing competition policies that account for the heterogeneity of markets in the magnitude of Schumpeter competition.

The Chapter is co–authored with Uwe Cantner and Ivan Savin. The contribution share of the author is 40 percent.

1.2.5 Chapter 6

Chapter 6 deals with another, different case of linked markets. In this case, the concept of market is conceived in a broader sense as 'domain'. The academic domain is the one taken into consideration and linked to the domain of application and commercialization of its output. In short, the Chapter provides an experimental analysis of policy interventions favoring the investment and transfer of knowledge from Academia to *academic spinoffs*. Inspired by the example of the trustful relation established between Stanford University and Google and by relevant policy schemes such as 'Small Business Technology Transfer' (SBTT) in the United States and '*Existenzgründungen aus der Wissenschaft*' (EXIST) in Germany, the focus of the Chapter is set on the study of the effects of different public policies on academic knowledge commercialization, as well as on the long–run effect of these policies.

Governments have indeed a considerable interest in intervening in–between the linkage connecting Academia and Industry, given the expected broad societal benefits of knowledge commercialization. Interventions tailored to foster academic knowledge commercialization usually take the form of subsidy policies consisting of two stages: In the first stage, a University receives a subsidy to support the spinoff creation process. In a second stage, it is the successful spinoff to be directly subsidized. Alternative forms of policy such as non–monetary communications and suggestions about the level of investment considered desirable by the policy–maker are rarely considered, though they may be implemented with non–negligible savings of public resources. Moreover, policies of the kind described above focus on the short term effects of interventions disregarding the long term, post–intervention costs.

In the Chapter we provided a novel contribution by dealing with both the issue of alternative policies evaluation and the long–run consequences of interventions. A model is proposed in order to guide hypotheses derivation that summarize the expected effects of different types of policy. We tested the hypotheses using the responses of experimental subjects in the Laboratory. In the experiment we employ a multi–period version of the trust (investment) game (Berg et al., 1995), where 'trustors' investments out of their allocated endowment proxy Academia engagement in commercialization activities and 'trustee' reciprocal transfers capture the feedback relations from Industry to Academia. The experimental design is rather original and represents another novel contribution of the Chapter to the existing literature. The policies considered in the contribution are i) a subsidy conditioned to an high threshold of needed minimum contribution, ii) a subsidy conditioned to a low threshold of needed minimum contribution, and iii) a targeting policy suggesting a level of contribution 'desired' by the policy–maker.

The main result of the study is that monetary incentives (subsidies) do not significantly increase investment levels, while the targeting policy in which authorities suggest a desired behavior increases the investment activity during the intervention and does not have long–run (post–intervention) detrimental effects. For what regards monetary policies involving subsidies, two implications can be drawn: Experimental subjects tend not to follow the subsidy policy; if they do, they send mostly the lowest amount required to obtain the subsidy. Moreover, monetary policy is ineffective in influencing the investment rate not because the monetary dimension itself, but rather due to the fact that the subsidy is *conditioned* on a given action. In fact, experimental subjects acting as trustee, that unconditionally receive a subsidy given trustors investments decisions, do not show significant differences in their trustworthiness level as compared those who do not receive the subsidy.

As a policy implication, the Chapter suggests policy–makers to grant more consideration to communication and targeting policies. These types of policy may be a more economic — and non–detrimental in the long–run — tool to reinforce the link between the domains of Academia and Industry.

The Chapter is co–authored with Igor Asanov. The contribution share of the author is 50 percent.

1.2.6 Final Overview

Through a set of Chapters ranging from the Microeconomics of GPTs and heterogeneous technical change to the extensions of market selection principles and policy measures fostering the linkage between Academia and Industry, the Thesis provides a contribution to a nascent Economics of Linked Markets. The limitations of the Thesis are outlined in the conclusions; in any case, by studying the dynamics of markets and technologies when GPTs are involved, when innovation and selection take place in value chains, and when policy can ease in different ways the commercialization of knowledge from the academic to the market domain, room is open to develop a more complex and networked view of economic dynamics.

Chapter 2

A New View of General Purpose Technologies

2.1 Introduction: General Purpose Technologies

Technologies are not all alike. Some of them add incrementally to the economic and productive system; other technologies, instead, have a revolutionary impact: they impose on the economy a new structure of dependencies and complementarities (they produce a *rejuvenation*, in Perez (2004) terms) and exploit physical phenomena in new ways Arthur (2009). The economy restlessly reconfigures itself around these technologies, producing as a result an open–ended evolutionary process of change. Recently, the economic literature has started to recognize the heterogeneity that characterizes the nature of different technologies introducing the concept of General Purpose Technologies (hereinafter GPTs). The aim of this Chapter is to critically guide the reader into the topic, offering also a novel perspective on this field of studies.

The awareness that major technological changes are the main determinants of cyclical and non–linear patterns in the evolution of an economy is not a monopoly of the literature on GPTs. Conversely, the idea is at the core of the long–standing research on Long Waves (Silverberg, 2003) and dates back to end of the Nineteenth century, when scholars started to abstract from the case–specific theories of economic crisis, generalizing formal models of trade cycles (in the United Kingdom), business cycles (in the United States) and *Konjunctur* (in Germany) (Besomi, 2010). Further back in time, already Shakespeare wrote that 'there is a tide in the affairs of men, Which, taken at the flood, leads on to fortune'[1], highlighting the importance of economic fluctuations. The work of Kondratieff (Kondratieff and Stolper, 1935) and Schumpeter (1939) — especially his often misrepresented and re–invented hypothesis on clustering of innovations and creative destruction — are the literature's milestones that paved the way for a wide range of theoretical and empirical attempts to identify long–wave patterns in economic history.[2]

From the brief perspective outlined above, the research on GPTs appears more as a contemporary endeavor to empower endogenous growth theory with the analytical tools to explain economy–wide fluctuations, than a conceptual novelty.[3] The GPT 'instantiation' of the more general topic of long run fluctuations is nevertheless quite interesting and important for innovation scholars, since the narrow focus of GPT theories is on the nature of technology and its effects on productivity dynamics, capital accumulation and innovative activities rather than on the explanation of the wave in itself or on the analyses of the systemic consequence of techno–economic paradigm changes (Perez, 2004).[4]

Before dealing with the definition of GPTs, however, it is worth recalling two more issues. The first helps us to frame GPT models in the literature:[5] the similarity between the concepts of GPT and radical innovations, macro–inventions (Mokyr, 1990), and shifts between technological paradigms (Dosi,

[1] Cited by Jevons in his Political Economy (Chapter XIV, about the periodicity of Industry)

[2] For a comprehensive overview, see Silverberg (2003)

[3] For the sake of clarity, in the Chapter we use the term endogenous growth theory to refer to two sets of models, one inspired by the 'AK' approach and Paul Romer's contributions (Romer, 1986, 1990), the other collecting under the label of 'Schumpeterian growth models' quality–ladder and R&D–based models such as Aghion and Howitt (1992), and the quasi–endogenous literature started by Dinopoulos, Segerstrom and others (Dinopoulos and Sener, 2007).

[4] Alternatives to GPT–based modeling of economic fluctuations and Long Waves are, for example, Jovanovic and Rob (1990) formal account of Schumpeterian cycles, technological opportunities, extensive and intensive search.

[5] For a complete taxonomy see (Coccia, 2003, p. 11).

1982) is evident. Therefore, as for theorists to identify a clear–cut boundary between macro and micro or radical and incremental innovations represents a challenge, a similar shortcoming affects the selection of appropriate criteria to identify the technologies that actually are GPTs. We deal with such issue in the next pages, since this is a relevant point for our claims.

The second issue is methodological. GPT–based modeling brings together the analytical framework of neoclassical growth theory, that is linear in nature,[6] and the one of heterodox growth theories (Setterfield, 2011) that traditionally paid more attention to the cycling behavior of economic aggregates. This 'refinement' of the simpler approach to technological change adopted by mainstream growth theory, where a generic stock (a scalar) of 'ideas', knowledge, or technology interacts with a production function, is not the only modeling strategy available to economic theorists. As Goodwin puts it clearly in his treatment of the (non–linear) accelerator principle as the determinant of cycles

> (a)lmost without exception economists have entertained the hypothesis of linear structural relations as a basis for cycle theory (. . .) whether we are dealing with difference or differential equations, so long as they are linear, they either explode or die away with the consequent disappearance of the cycle or the society. One may hope to avoid this unpleasant dilemma by choosing that case (as with the frictionless pendulum) just in between. Such a way out is helpful in the classroom, but it is nothing more than a mathematical abstraction (. . .) Mention should also be made of the fact that there exists an alternative way out of the dilemma — that of an impulse–excited mechanism. There are two basically different classes of such mechanisms to be distinguished. (a) There are the synchronized systems of which the most familiar is the ordinary pendulum clock. (. . .) The wider system (. . .) is a particular type of nonlinear oscillator since it is autonomous and maintains a uniform cycle independently of initial conditions. (b) Significantly different is a system subject

[6] In fact, following Solow (1997), a theory of growth should not explain short term fluctuations but only the long–term potential trajectory of an economy.

> to random shocks. Here the mechanism itself is damped, but an outside, unexplained source keeps it going, and in this sense it is not a complete theory, for the source of maintenance lies outside the theory (. . .) (Goodwin, 1951, p. 2)

GPTs models fall under point (b), since a new GPT — also in advanced models inspired by Goodwinian Lotka–Volterra dynamics (Fatás-Villafranca et al., 2012) and even more in the 'classic' modeling approach to GPTs (Helpman, 1998) — arrives from outside the system, when it is modeled directly as an exogenous variable (in a deterministic or stochastic fashion, as we deepen further later) as well as when it results indirectly from endogenous knowledge accumulation. GPTs are then only shocks revitalizing an economy characterized by the tendency to 'relax' in a steady–state equilibrium growth.

In this Chapter, we argue that in addition to Goodwin's choice (a), that of using non–linear systems as modeling workhorse, it is possible to frame a more complex alternative (c), where the emergence of a GPT is the result of localized and directed knowledge interactions, exploitation of technological opportunities and coordination in production across heterogeneous and evolving industries and firms. What we propose is an evolutionary and Schumpeterian account of GPTs, where the innovative change comes *from within*, producing differential growth.

The Chapter proceeds as follows. Section 2.2 critically overviews the criteria to define and identify GPTs. Section 2.3 describes the most relevant GPT–based analytical models. Section 2.4 outlines a 'Microeconomics of GPTs' by looking at GPTs from a micro and meso level of analysis. Section 2.5 concludes.

2.2 Defining and Identifying GPTs, Engines of Growth

The strand of literature dealing with GPTs has been initiated by David (1990) and especially by Bresnahan and Trajtenberg (1995). In the latter, GPTs are defined as key technologies, fully shaping a technological era, and 'characterized by the potential for pervasive use in a wide range of sectors and by their technological dynamism' (Bresnahan and Trajtenberg, 1995, p. 84). GPTs execute some *generic functions* such as 'continuous rotary motion' or 'binary logic' and act like platforms, 'enabling mechanisms' for complementary innovations in downstream sectors, leading to the transformation of the economic system as well as to generalized productivity gains. Rosenberg and Trajtenberg (2004) identify more precisely the properties of a GPT in their historical case study of the Corliss Steam Engine in the U.S. (emphasis added):

> first, (a GPT) is a technology characterized by *general applicability*, that is, by the fact that it performs some generic function that is vital to the functioning of a large number of using products or production systems. Second, GPTs exhibit a great deal of *technological dynamism*: continuous innovational efforts increase over time the efficiency with which the generic function is performed, benefiting existing users, and prompting further sectors to adopt the improved GPT. Third, GPTs exhibit '*innovational complementarities*' with the application sectors, in the sense that technical advances in the GPT make it more profitable for its users to innovate and improve their own technologies. (Rosenberg and Trajtenberg, 2004, p. 65)

Therefore, on the 'input side', that of technical features, what makes a technology a GPT is its i) *general applicability*,[7] ii) *technological dynamism* and iii) *innovation spawning*, as Jovanovic and Rousseau (2005) name the innovational complementarity feature of GPTs. Quite similar features are listed in other definitional exercises, to be found in the collection of papers edited by Helpman (1998) and in the studies of Lipsey et al. (2005), Guerrieri and

[7]General applicability is sometimes replaced in the literature by the term 'widely used' — see Bresnahan and Yin (2010), indicating a tendency in the theoretical analyses of GPTs to loosen the concept in order to group a wider range of technologies under the definition of 'general purpose'. An additional criticism that we will not address here concerns the definition of general applicability itself, which in the GPT–literature is always conceptualized in relation to the number of application sectors that use the GPT. Alternatively, general applicability can be interpreted as the feature of 'doing nothing in particular' (Simon, 1987), pointing more to the breadth of *functions* a technology can potentially operate, abstracting from the connections with other sectors or technologies.

Padoan (2007) and Jovanovic and Rousseau (2005). The latter, in particular, testing empirically similarities and differences between two popularly recognized GPTs, electrification and ICT, adds six other 'symptoms' of a GPT derived from theoretical models, and holding also (even with different magnitudes for the two technologies) from empirical evidence (Jovanovic and Rousseau, 2005, pp. 1203–1204). These further features can be considered the 'output side' characteristics of GPTs: i) *productivity slowdowns*, due to learning effects and to the allocation of productive resources to develop the new compatible and complementary capital required to use the GPT; ii) *rise in the skill premium*, as the increase in demand for skilled labor should facilitate and shorten the learning process; iii) *rise in entry, exit and mergers* as a measure of reallocation of resources; iv) *initial fall of stock prices*, due to the acceleration in the rate of obsolescence of old capital vintages caused by the adoption of the new GPT; v) *changes in market shares favoring young firms*; vi) *rise in the interest rate and worsening of trade balance*, since assets reallocation, by reducing output, pushes demand and consumption to search for foreign markets.

The productivity slowdowns on the one hand and the consequent time lag needed for a new GPT's productivity improvements to show up in the data on the other, can be seen as one of the explanation for the so–called Solow paradox (Basu and Fernald, 2007; Solow, 1987). This is in fact also the main outcome generated by the first cohort of GPT–based growth models, built around the concept of 'the time to sow and the time to reap' (Helpman and Trajtenberg, 1994). Fluctuations in productivity, together with the acknowledgment that technological progress is uneven, 'comes in bursts' (Jovanovic and Rousseau, 2005, p 1221) and is pervasive with different degrees, can be considered the main motivation leading to the development of GPTs literature.

We envisaged earlier in the Chapter that the problem emerging from this kind of definitions is one of *identification*. The issue is problematic from an ex ante point of view (can one infer the GPT nature of a technology since its very introduction in the market?[8]) as well as from an ex post viewpoint

[8] In the literature, a GPT is never seen as an 'emergent property' of market and technological interactions.

(can one classify under the label 'GPT' what has been generically recognized as a radical innovation?). Which technology is a GPT and which one, instead, is not? The knife–edge distinction, here, is between those scholars who recognize only two or three GPTs since the industrial revolution (the steam engine, electrification, and the more questioned ICTs) and see them as singularities or extreme cases of radical innovations ('epochal innovations', as Rosenberg and Trajtenberg (2004) rename them), and those who expanded the list to a much more wide range of technologies. As we will show in the next paragraph, the first generation of GPT–based growth models,[9] employing one GPT per period, is closer to the first interpretation, while recent models tend to a more generous interpretation of the notion. Empirical literature made some steps forward in solving the identification puzzle, however, the results are useful only for what concerns measurement issues and do not allow to distinguish clearly between GPTs and 'simple' radical innovations.[10]

David and Wright (1999) stress precisely the ex post identification point when, after another enumeration of the properties characterizing a GPT, they criticize the growing number of technologies labeled 'general purpose' by growth and innovation scholars:[11]

> One has only to consider the length of such proposed lists of GPTs to begin to worry that the concept may be getting out of hand. History may not have been long enough to contain this many separate and distinct revolutionary changes. On closer inspection, it may be that some of these sweeping innovations should be better viewed as sub–categories of deeper conceptual

[9] Except the very first model of Bresnahan and Trajtenberg.

[10] For example, Jovanovic and Rousseau (2005) cite the study of Cummins and Violante (2002) who — adopting a capital–embodying perspective on technological change — 'classify a technology as a GPT when the share of new capital associated with it reaches a critical level, ad if adoption is widespread across industries'. Another empirical choice is the one needed to identify the beginning of a GPT era. Again, Jovanovic and Rousseau set it to 'the point in time when the GPT achieves a one–percent diffusion in the median sector'. Other empirical analyses make use of patent data to 'uncover' GPTs and to forecast new potential candidates for this role (Hall and Trajtenberg, 2004; Youtie et al., 2008; Feldman and Yoon, 2012).

[11] For example, Lipsey et al. (2005) suggest five technological classes into which to group different GPTs. These are materials, ICTs, power sources, transportation equipment and organizational forms.

> breakthroughs in a hierarchical structure. Alternatively, particular historical episodes may be fruitfully understood in terms of interactions between one or more GPTs on previously separate historical paths. (David and Wright, 1999)

Although subscribing the David and Wright's comment, we have to admit that a heuristic to discriminate between GPTs and non–GPTs is still to be found. In Section 2.4 we will make an attempt to characterize some of the sources and conditions that can lead to the ex post prevalence and pervasiveness of a GPT.

2.3 Modeling GPT–based Economic Growth

It is useful to distinguish between a first and a second generation of GPT–based formal models. The first generation includes, in addition to the Bresnahan and Trajtenberg (1995) seminal paper, the models collected and reprinted in Helpman (1998), in particular the two contributions by Helpman and Trajtenberg and the one by Aghion and Howitt, who introduce GPTs into a modeling framework *à la* Grossman and Helpman (1991). After an interval of approximately five years, the research on GPTs restarted with the studies of van Zon et al. (2003), Carlaw and Lipsey (2006, 2011), Guerrieri and Padoan (2007), Harada (2010) to end up with the recent contributions by Bresnahan (2010, 2012) and Rainer and Strohmaier (2014). The list can be enlarged by at least another model, that of Fatás-Villafranca et al. (2012), which deals with major innovations, cycles, Long Waves and technological eras though without explicitly referring to GPTs. In what follows, we review only some of the models, that we consider providing the most representative and relevant contributions.

The rationale for distinguishing between the two different cohorts of models is both conceptual — considering the diverse perspectives on the nature of GPTs — and chronological, since the second generation of models belongs to a later reprise of the topic after its rapid success and even faster decline at the end of the Nineties.

The Bresnahan and Trajtenberg (1995) model (hereinafter BT) cannot properly be considered a growth model, since it stems from a micro/industrial organization–framework and it captures with a strategic game the interaction between two kinds of sector, the (single) GPT sector and a number of application sectors (AS). The focus in this model is not on the GPT itself, but on the pure incentive–based 'dual inducement mechanism' at work between GPT and ASs. In short, GPT and ASs play a joint innovation game: an increase in the quality of the GPT (representing what we called 'technological dynamism') incentivizes the ASs to increase their technological levels (this is the 'innovation complementarities' property of GPTs) and this, in turn, induces the GPT sector to further advance its technology. The linked payoffs of GPT and ASs produce a mutual feedback leading to multiple Nash equilibria. This particular structure of interaction relies on two kinds of externalities that, from a welfare point of view, lead to a social rate of return greater than the private rates of return: one is a vertical externality, related to the connected and hierarchical payoffs structure of the GPT and ASs as well as to the role of imperfect information flows and appropriability between the sectors. The other is a horizontal externality focusing on the role of demand, since the more ASs exist in an economy, the more valuable is the GPT. The presence of the horizontal externality reinforces the importance of public subsidies and public demand (procurement). The implication of the BT model is that 'the coordination problem between technology–innovating and technology–using industries' (Hall and Trajtenberg, 2004) cannot be solved optimally in a decentralized market system.

The Helpman and Trajtenberg (1994) model (hereinafter HT) draws on BT's insights on GPTs and inject them into a fully–fledged endogenous growth model assuming agents' perfect foresight. Here GPTs become the main determinants of long–run macroeconomic dynamics. Output is produced with a GPT and a continuous set of components that have to be compatible with the general technology and that are produced by innovators in a monopolistic competition framework. New GPTs arrive in a deterministic way at predetermined time intervals of equal length, generating a symmetric cycle with two (or three, in a special case) sub–phases. In the first phase, the old GPT is used to produce final output while resources and labor are allocated to R&D in order to develop components for the new GPT. In the second phase, starting after a minimum threshold of components has been produced, the development of components continues but the new GPT is adopted, fostering productivity. During the first phase of the cycle, real GDP declines as wages increases, while the other way round happens in the following phase. This mechanism has been successfully summarized by the expression 'a time to sow and a time to reap', and has been extended by the same authors in a follow–up paper (Helpman and Trajtenberg, 1996) that keeps the formal structure but allows for the existence of many sectors. The order of adoption of the GPT across the sectors between early adopters and laggards, and therefore the diffusion process of the GPT technology, can lead to multiple long–run equilibria. Policy implications are derived from the model — in particular, the advice to intervene in order to shorten the first phase of the cycle — but an empirical operationalization of the model to test its predictions results problematic.

The Aghion and Howitt (1998) model (hereinafter AH) starts from HT's basic formulation, stressing its limited empirical relevance for what concerns two issues: Firstly, the representation of *the size of the slump*, since 'all of the decline in output is attributable to the transfer of labor out of manufacturing and into R&D. But since the total amount of R&D labor on average is only about two and a half percent of the labor force, it is hard to see how this can account for change in aggregate production of more than a fraction of a percent.' (Aghion and Howitt, 1998, p. 55). Secondly, *the timing of the slow–down*, that in the previous model follows immediately the arrival of the new GPT. Therefore, AH adds to the HT model both a Schumpeterian flavor by making the arrival of GPTs stochastic realizations of a Poisson process, and a more realistic representation of the adoption process by taking into account 'social learning'. The AH model divides the cycle into three phases, instead of the two considered in HT: 'first, the economy wide GPT must be discovered. Second, a firm in that sector must acquire a "template", on which to base experimentation. Third, the firm must use this template to discover how to implement the GPT in its particular sector' (Aghion and Howitt, 1998, p. 63). The role of social learning is relevant here: a firm (an industry) can move from phase zero to phase one — the acquisition of the GPT template — via independent discovery (depending on a Poisson process) or through imitation, whose likelihood to occur is a probability given by a cumulative binomial distribution. The transition from phase one to phase two, then, requires the allocation of labor resources to R&D activities, with a rate of success that depends on another Poisson distribution. Additionally, AH provide extensions of the model that include skill differentials, wage inequalities and their relationship with technological change and with the size of the slump generated by the arrival of the GPT. Also the effect of the innovation–wave arrival on capital obsolescence is analysed.

Despite conceptual or analytical differences, the first generation of GPT–based models share a common assumption: the GPT is recognized ex ante as a general purpose technology. In BT, it is the 'first mover' that incentivizes application sectors to exploit innovation complementarities and starts the dual inducement mechanism. In HT and in AH an explicit assumption is made about the impossibility to develop new components before a new GPT has arrived. By having ex ante knowledge about the existence of a new GPT, economic agents are left only with the possibility to decide on the allocation of resources to research on the basis of their expected profit. The picture is quite simplified with respect to a reality of continuous technological change, with competition (Arthur, 1989), diffusion and selection happening in an uncertain environment that opens room for the role of risk–taking entrepreneurs.

The model of van Zon et al. (2003) is thus assigned to the second generation of models, although it is just a modification of the Romer model (and so it may appear to belong to the first generation), not only for a chronological reason, but mainly because it departs from the assumption that GPTs are identified ex ante. It is also the first model that allows for co–existing GPTs. The model assumes two types of stochastic (Poisson) R&D processes: a basic R&D sector, which produces 'core' technologies (the GPTs), and an applied R&D sector, producing 'peripherals', corresponding to HT components. Both R&D sectors are subject to decreasing returns, so after the arrival of a core technology the economic incentive — and the labor force — switches to the production of peripherals, and the other way round. The fundamental novelty of the model resulting from its solution using simulation methods, relates to the possibility that some cores become 'failed' GPTs if few or no components are developed for them. Failed GPTs remind us that 'during the innovation process, the actual pervasiveness of an innovation when and if it arrives can only be guessed at' (van Zon et al., 2003, pp. 8–9). A GPT is an 'ex–post mental construct', deriving from the evidence that a particular technology is capable to execute a wide range of (old and new) productive functions in the economy. To assume the existence of a GPT ex ante can lead to a limited comprehension of pervasive GPT–based economic growth.

Carlaw and Lipsey (2006) (hereinafter CL) extend the idea of the van Zon et al. model, proposing an out–of–equilibrium three (competitive) sectors model, where the appearance of a GPT is driven by an endogenous mechanism. The three sectors, each represented by a specific production function, are: i) *a fundamental research sector* that accumulates a stock of basic knowledge and produces the GPT; ii) *an applied R&D sector* and iii) *a consumption sector*. The latter sector produces consumption goods with a productivity level derived from a share of the knowledge generated by the applied R&D sector. In turn, the applied R&D sector accumulates knowledge with a degree of effectiveness that depends on the stock of knowledge available in the fundamental research sector. Finally, the fundamental research sector creates basic knowledge with a productivity that depends on the share of applied knowledge that is not directed to the production of consumption goods. The basic knowledge generated by the fundamental research sector is accumulated at every period as a 'potential' stock, but can be used only when a new GPT appears. The arrival of a new GPT is again stochastic and it relies on a slightly more complicated mechanism than the Poisson process used in other models: two (left–skewed) Beta distributions generate two random values; the first is compared with a threshold–value and, if bigger, the GPT appears. The second random value resulting from the remaining Beta distribution calibrates the amount of potential basic knowledge accumulated before the arrival of the new GPT that becomes usable with the appearance of the GPT. The model is closed specifying consumers' expectations, the maximization problem and the resulting resources allocation that is assumed to be conducted by a social planner. The results of the model simulation show that economic growth persists as long as the fundamental knowledge sector is 'feeded' by GPT, that restlessly 'rejuvenate' the system and produce waves (spikes) in the allocation of resources and in the output produced. CL model is further developed in a succession of studies featuring multiple and coexisting GPTs being active in the economy (Carlaw and Lipsey, 2011). There, the fundamental research (GPT) sector is divided into different technological categories, while the applied R&D sector is represented by many research facilities. The picture of economic evolution offered by such model becomes quite realistic, however at the price of a stretching of the very concept of GPT. As mentioned above in early warning of David and Wright, the modeling of plenty of co–existing GPTs can be at odds with the aim to describe the role played by 'revolutionary technologies'. Further, the promising idea of the van Zon et al. model to challenge the assumption of an ex ante identification of GPTs is lost in the CL formulation, which considers only the stochastic modeling of the GPTs arrival.

Before concluding this overview Section, another critical point should be added: in the models presented, as well as in the Goodwinian model of Fatás-Villafranca et al. (2012), the arrival mechanism of a new GPT depends on the accumulation of a certain quantity of knowledge, either due to the optimal allocation of resources to research or to routinized decision–making. Technological eras follow one another because of the collection of a generic, non–well–specified commodity labeled 'knowledge'. Once one realizes that the evolution of knowledge is something more complex, localized, purposeful and 'sticky', the modeling strategy used in the existing literature to represent the arrival of GPTs can results too stylized. To capture this more sophisticated issue, a new view of GPTs should, therefore, be grounded on a finer–grained level of analysis, opening room — as suggested in the next Section — for a Microeconomics of GPTs.

In spite of some of the theoretical developments overviewed above, we think that the initial approach followed by Bresnahan and Trajtenberg remains the most promising starting point to deal with GPTs, since it focuses on the micro– and meso–economic interaction structure between GPTs and their applications rather than on the black box assuming a certain data generating process determining the GPT arrival. Two recent contributions by Bresnahan (2012) and Bresnahan and Yin (2010) extend our understanding of GPTs in this direction. The paper of Bresnahan and Yin (2010) deals with the role played by heterogeneous consumer demand. GPTs replacement is the outcome of the process through which ‘growth bottlenecks’, which are generated by the inertial (locked–in) trajectory of technical progress within the established GPT and ASs, are overcome thanks to the presence of unserved demand that searches for new GPTs. The study of Bresnahan (2012) returns instead to the supply side of the story to analyze the conditions for the emergence of a ‘GPT cluster’, that is the ensemble of a GPT and its linked AS. Here the role played the ‘recombination’ of different technologies and the ‘re–use’ of the resulting knowledge are key to understand the establishment of a GPT. Three stylized processes are highlighted: i) *planned initiative*, the classical hierarchical interpretation of GPT, where the introduction of a GPT induces the development of complementary innovations; ii) *technological convergence*, where specific technologies are invented first — even lacking the knowledge about their potential linkages — and these inventions raise the expected profit of inventing a GPT able to connect and recombined the already existing technologies; iii) *inversion*, when a ‘specific’ innovation increases the value of inventing a GPT whose introduction, in turn, increases the incentive to introduce a new specific technology.

The last two contributions we discussed, even if they do not tackle the identification problems (a GPT is identified as such ex ante, right from the model setup, and in all the three scenarios outlined), pave the way for an analysis built on micro and meso arguments. An uneven and self–reinforcing (or self–reducing, as it could be possible in the case of a vicious circle of disincentives for innovative activities both in the GPT and in the AS) interaction between a hierarchy of technologies is a perfect point of departure for a Schumpeterian and evolutionary account of GPTs. The recognition of the role of technological specificities and opportunities (in the cases of convergence and inversion), together with the role demand plays in the ‘coordination game’ of GPTs’ introduction and diffusion, takes us very close to the conceptual building blocks used by the literature on Industrial Dynamics and Microeconomics of Innovation.

2.4 The Microeconomics of GPTs: Prevalence and Pervasiveness

To summarize the discussion so far, we quote a passage from Bresnahan (italics is ours):

> one goal (*of studying GPTs*) lies in growth macroeconomics, to provide an explanation of the close link between whole era of economic growth and the innovative application of certain technologies, called GPTs, such as the steam engine, electric motors, or computers. Another goal is in the microeconomics of technical change and proceeds by differentiating between innovations of different types. The incentives and information related to the invention of GPTs themselves, may differ from those related to the invention of applications; another example would be the incentives and information related to an established GPT with successful applications in contrast to earlier stages. A third goal links the macro and the micro. Can we understand the linkages between aggregate economic growth and the incentives and information structures related to particular inventions and to their application to particular uses and sectors? (Bresnahan, 2010, p. 763)

In this paragraph, we look at GPTs from a microeconomic point of view. The discussion of GPTs within the growth literature has shown that the appearance of GPTs in the models is taken as rather exogenous and their influence on other industries and sectors in an economy and hence their pervasiveness is taken as given. Certainly, to analytically proceed in this direction can be justified in two ways. First, it is for the purpose of modeling convenience allowing for an analytical solution. Secondly, the discussion of Long Waves of economic development has repeatedly highlighted the occurrence of fundamental technologies. The emergence of these fundamental technologies (as well as the approach of Long Waves in general) still is a phenomenon not well understood, despite several attempts in the Eighties and Nineties (Haag et al., 1987; Weidlich and Haag, 1983) searching for an explanation. In view of that state of the art, especially the assumption about the exogeneity assigned to GPTs in macro modeling seems to be not too farfetched.

Our stance in this discussion is, however, to go further and to highlight some directions of analysis that allow to better grasp and understand the phenomenon of GPTs. For this purpose we combine the insight by van Zon et al. (2003) of a GPT as a 'ex post mental construct' with considerations on early indicators of the emergence of GPTs. Hence we attempt to come closer to the 'origins' of a GPT. By this we certainly follow Arrow (1991) in admitting that '...it is hopeless to develop a model which will genuinely predict innovations' and in claiming that those models and the considerations behind them will provide '...some useful idea of the average rate of technological change, of the degree of fluctuations and the kinds of surprise that we may find in the future. We cannot, of course, predict a surprise; that is a contradiction in terms. But we can predict the kind of surprises that might occur'. On this basis we suggest to enrich the approaches to GPTs by a micro and a meso level analysis and draw attention to approaches which address path dependency, technology competition and dominant designs, as well as collective innovation and sectoral interdependencies. A look at the characterization of GPTs from a microeconomic point of view again already indicates some avenues to follow.

As discussed abouve, an attempt to summarize various definitional exercises on GPTs in the literature leads to the following three characteristics: i) Pervasiveness: A GPT should have an impact on technical change and productivity growth across a large number of uses/industries; ii) Improvement: A GPT should experience a wide scope of improvement and elaboration in its own industry; ii) Innovation spawning: A GPT should lead to product and process innovation in a broad range of uses / application sectors. These characterizations are based on an implicit assumption, namely that the technology under concern, the GPT, is a prevailing technology, it exists for a longer period of time, it is accepted on a broad scale and for these reasons it impacts on an economy in a pervasive, improving and innovation generating way. Hence, the conditions for a broad usage of a GPT in an economy are of interest but neither her sources nor the conditions of her prevalence. What are the sources of prevalence and of pervasiveness so much at the core of GPTs? What can be said beyond addressing an exogenous source?

2.4.1 Conditions for Prevalence

The prevalence of a technology is given by her persistency over time. In other word, such kind of technology is unlikely and difficult to be challenged by new alternative technologies — it seems to be incontestable, at least for some time. Instead of taking that feature as given we have to think about mechanisms and determinants just providing for prevalence. To accomplish that let us first look into the reasons for a technology to be incontestable.

According to David (1985, 1987) this prevalence is the result of a coordination of agents' choices on a specific technology. The outcome then is a specific allocation which is rather stable over time. Three conditions lead agents to coordinate their choices and also lend persistence to the resulting allocation: i) the technical interrelatedness of system components; ii) quasi–irreversibility of investment (or, more generally, switching costs); iii) positive externalities or increasing returns to scale.

The technical interrelatedness of a system (i) appears to be an aspect very much out of the economic realm. Chemical and physical laws as well as engineering types of relationships presumably determine which kinds of technologies fit together, which ones may be substituted, and which complementarities cannot easily be challenged. If we consider GPTs as the core of such kind of a system then the explanation for their prevalence is a rather technical one.

The quasi irreversibility of investment and related — often very high — switching costs (ii) extend the previous argument and translates it into economic cost terms. The technical interrelatedness (i) could as well be expressed in cost terms: the switching costs, related to the resources required for exploring new chemical and physical laws or engineering relationships, which allow for breaking up the interrelated system, are very (if not infinitely) high. In other cases, it is the systemic dimension of the supply of the goods and services related to a certain technology which protects against the challenges of new invader technologies — the combustion engine for automobiles and the accompanying system of fuel stations and fuel logistics just being a point in case. Combined with these investments are mutual dependencies — not only of a technical nature but also in terms of relative prices — which contribute to the prevalence of the core technology. As long as relative factor price changes remain in a certain range, switching costs to new alternatives prevail high and secure the persistency of the existing technology.

Another aspect of a technology, partly related to the aforementioned systemic aspect, addresses the existence of positive externalities or increasing returns to scale (iii) in the use of a certain technology. These increasing returns may arise either on the supply side of a market as a result of learning effects (learning by doing or by using) or on the demand side as a result of positive network (or agglomeration) externalities that raise the benefits of a technique, product, or location for each user as the total number of users increases. Learning by doing, allowing the efficiency a certain technology to increase the more it is used, sustains competitiveness and dominance of the dominant technology. The positive network effects related to customers' adoption of a certain technology are based on idea that the individual benefits a customer enjoys depends positively on the number of other customers — as is the case in telephony, video system or in computer software. These supply and demand side based externalities already protect the established technology against possible invading new alternatives.

At least the second and third of the conditions above — irreversible investment and increasing returns — indicate already that the effects on prevalence are realized not at a single point of time but rather dynamically. In either case it is a positive feedback from the macro state of the system (high level of front–up investment, high number of adopters) to the choices of individual agents, eventually resulting in de facto standardization on a single technique. In the words of David (1987), effects of path dependence are prevailing here.

Taking into account the dynamic dimension of the conditions for prevalence quite naturally leads to considerations about the sources of prevalence. Hence, the mechanisms that sustain prevalence are also the ones leading to dominance. Or to put it in reverse order, observing a technology that in competition appears to dominate due to positive feedbacks allows the conclusion that this technology will stay dominant for a certain longer period.

2.4.2 The Dynamics Towards Prevalence

For understanding innovation and technology competition, insights from Industrial Dynamics and the inherent innovation, learning and knowledge dynamics are useful. This literature informs about possible mechanisms, conditions and structural dynamics on which the development or the appearance of a standard or a dominant design is based.

At the core of the further discussion are approaches in Industrial Dynamics. This field of research established by formulating major criticism to the approaches in industrial organization tackling the traditional issues related to the Neo–Schumpeterian hypotheses, namely the question whether large (monopoly) firms or small (competitive) firms are the major drivers of innovative activities and the resulting economic development. The inconclusive empirical evidence on these hypotheses induced a research agenda that considers the analysis of industries and the innovative activities herein to necessarily take into account innovation and technology dynamics. The resulting competition between differently innovative firms or different technologies is a major driving force in shaping industry and market structures.

A GPT in this context can be considered the result of competing new technologies or the successful challenge of an old (GPT?) technology. The mechanism behind is path dependent, presumably leading to the establishment of a standard or a dominant design — both resembling the characteristics of dominance over alternatives.

> A dominant design in a product class is, by definition, the one that wins the allegiance of the marketplace, the one that competitors and innovators must adhere to if they hope to command

> significant market following. (Utterback, 1996)

Compared to a GPT, a dominant design is just defined more from the generating side, in the sense of where it comes from and under which circumstances it appears. About its further effects not much is stated except that it is useful as well as widely accepted and used. In this sense, it complements the concept of GPT just from the generating side and combining both may help understanding better the appearance of GPTs.

As to the emergence of a dominant design, it is a competitive process of trying out the basic features of the dominant design:

> Prior to the appearance of a dominant design many of its separate features may be tried in varied products which are either custom designed or designed for a particular and demanding market niche. (Suarez and Utterback, 1995, p. 118)

The industry life cycle literature — dealing with the long-run development of industries — just applies the concept of a dominant design (Utterback and Suarez, 1993) to explain the transition from a phase in which the number of firms in an industry is increasing to the appearance of the so–called shakeout, during which the net entry is negative and a sharp decline in the number of firms is observed — then eventually leading to a phase in which the number of firm is constant (an oligopoly). The appearance of dominant design is here seen as the outcome of the competition between various different technological solutions during the phase of expansion.

Among the factors reinforcing this development of competitive selection — best technology compromise; cooperation; combination of sociological, political, and organizational dynamics; economies of scale in Murmann and Frenken (2006); similar firm level related factors as well as environmental factors in Suarez (2004) — sources of dynamic externalities or positive dynamic returns to scale are important in our context. In some literature these effects are related to path dependencies. Those may be connected to the size of the firm and the accumulated production experience or to demand side effects. In principle these externalities provide for additional benefits for a technology which is leading in terms of produced or sold or used units. Hence, a first mover advantage related to size (production volume) contributes to the dominance of a certain technology.

The effects of economies of scale (Klepper, 1997, 1996) and related learning economies draw from the fact that the more units have been produced or the more often a technology has been applied the higher is the contribution to productivity which materializes in lower unit costs (and hence lower prices) or higher product quality (and hence a higher quality/price ratio). Both contribute to the benefit a user can reap and hence contribute to the dominance of the technology concerned.

An equivalent argument can be formulated for the demand side. David (1985) and Arthur (1989) highlight the benefit of using/consuming a specific product depending on the number of other users. Due to random factors one technology will gain a larger share in the population of consumers accompanied with comparatively higher returns. The likelihood that next consumers will select just this superior technology increases and subsequently without further larger random shocks the technology with the small lead will win a dominant position. Over time, the technology which accidentally grasps a certain lead in market share will in the end come to dominate the market or industry. Deviations from this outcome are either due to major stochastic shocks or the trespassing of a certain critical mass of adopters of a competing alternative (Witt, 1997).

Taken these arguments together, approaches addressing dominant designs inform about the competitive environment within which technologies strive for market dominance. One of the mechanisms or factors behind this process, namely dynamic economies of scale, coincides with the mechanism and conditions which provide for the prevalence of GPTs. On these terms, the emergence of a GPT and its prevalence seem to be intimately connected via the same kind of mechanism.

2.4.3 Conditions for Pervasiveness

The other core characteristic of a GPT, the pervasiveness in application and for further innovation, is related to i) her broad impact into other sectors and branches and ii) her relevance for further innovative activities there.

Pervasiveness appears on a first sight to be related to technological interrelationships, one of the conditions for a stable allocation formulated by David, and hence to be an exogenous factor. However, research into the innovation activities of firms, research institutes and other actors has delivered collective invention and innovation (Allen, 1983; von Hippel, 1987) as the mode of organizing these activities which has become more and more frequent over time. The basis for cooperating in innovation is risk and costs sharing on the one hand and knowledge exchange, access and sharing on the other. The context within which this collaboration appears is characterized by dispersed knowledge and competences which for the sake of coming to new solutions are required to be combined and interacted. This aspect becomes the more relevant the more complex is a technology to be developed and pursued.

Addressing again the literature on dominant designs[12] Liebowitz and Margolis (1995) show that collaboration in innovative activities as well as related strategies such as licensing of new ideas is conducive to the emergence of a dominant design. One may assign this property also to the appearance of GPTs. Moreover, the participation of several actors and their agreement on the best technological compromise (Abernathy and Utterback, 1978; Christensen et al., 1998) induces a broad acceptance which contributes to pervasiveness. In this context, the multidimensional nature and high development costs of many complex products rather naturally requires that several parties agree on cooperating and negotiating (Cowan, 1990; Rosenkopf and Tushman, 1992) in the technology to be pursued collectively.

Establishing a dominant design collectively brings about a certain pattern of further innovative activities. According to Anderson and Tushman (1990) the appearance of a dominant design is followed by innovative activities

[12] For example, Cusumano et al. (1992); Khazam and Mowery (1994).

which are of a rather incremental type. These incremental steps allow refining the basics of the dominant design and exploiting specific sectoral, industrial or agent specific opportunities the dominant design offers. As long as these opportunities do not get exploited completely, the pervasiveness of the dominant design/the GPT (as well as her prevalence) appears to be secured.

Certainly, the foregoing discussion of the emergence of a dominant design as a collective outcome and its persistence over time is quite neutral with respect to the breadth of this design. With breadth we mean the number of industries affected by the design, using it or working with it. In fact, the literature on dominant design is mainly focusing on industries and the competition among firms and/or technologies in these industries — hence it is an intra–sectoral analysis with the inter–sectoral dimension not taken on board. Applying these findings to our understanding of the pervasiveness of GPTs requires certainly taking on board the inter–sectoral dimension. To this end further research needs to be performed which will be informed by analyses on the technological relations between sectors (Cantner and Hanusch, 1999), the dimensions of related technological variety between sectors (Buerger and Cantner, 2011), as well as the policy designs in fostering collaboration in innovation (Cantner and Pyka, 2001).

2.5 Conclusion

The success of the GPT 'category' in economic theory is probably explained by the need to gather all the insights coming from a rich research trajectory on Long Waves and Business Cycles and to condense them into a workable 'mainstream' modeling exercise. However, both the very notion of GPT and the simplifying assumptions accompanying it in the macromodels we overviewed can be questioned. In this Chapter, we offered a 'new view of General Purpose Technologies', that builds on the classic as well as on the recent literature, enquiring more in deep the definitional problems related to GPTs and the conditions for their emergence, together with the characteristics influencing their prevalence and pervasiveness. A Schumpeterian and evolutionary view, pointing at the micro and meso level of analysis —

that of the dynamics of firms and industries —, is in our view the privileged perspective economists need to adopt in order to revitalize the theoretical and empirical study of GPTs. The similarities with the emergence of dominant designs and the relations with dynamics of increasing returns and path dependency in the choice between alternative technologies, together with insights taken from studies on collective inventions and cooperative ventures offer us a set of tools well suited to study the establishment of GPTs as a process unfolding in time, more than as a single, homogeneous shock.

Explaining GPTs is thus not a matter of technology 'arrival', nor does it require explicitly some inherent 'radicality' of the technologies under analysis. GPTs can be introduced in particular niches of the market or in specific industries and there they can be 'cultivated' or developed until, thanks to industrial interactions, demand pressures and technoligical competitions, they assume the role of core technologies, shaping the general configuration of production and the whole economy.

As Mokyr (2010) points out, 'major discoveries rarely arise *de–novo*, and what seems to us a breakthrough was only the last step in a long intellectual journey'. Our task as economist is to try to intercept the trajectory of this intellectual journey so to understand the possible alternatives an economic system can have at its disposal to increase the total welfare of the Society.

Chapter 3

Generalizing General Purpose Technologies

3.1 Introduction

The fertility of a theoretical concept depends on a number of factors, its diffusion being the result of positive feedbacks in use and adoption, or the fair reward for a superior effort in 'the art of successful theorizing' (Solow, 1956), meaning the capability to offer new insights independently of non–relevant details. Alternatively, the goodness of a theory — and, therefore, its likelihood to gain shares in the market for ideas — can be measured by its accuracy in providing correct predictions, despite the realism of its assumptions or premises (Hausman, 1989). In this Chapter, we assess the fertility and goodness of the theory of General Purpose Technology (hereinafter GPT), and suggest some ways to 'generalize GPTs'.

The concept of GPTs has been introduced in the early Nineties, pooling together diverse theoretical needs: to introduce heterogeneity in the conceptualization of technological change, to explain growth fluctuations and productivity paradoxes in a way different from both Long Waves theories and Business Cycles models, and tied to Industrial Organization and endogenous growth theorizing. Having David (1990) drawn a parallel between 'the Dynamo and the Computer', shedding some light on the historical and technological determinants of adoption–diffusion patterns and their effects on productivity, Bresnahan and Trajtenberg (1995) formally developed the concept of GPT. They did so in order to study the strategic interaction setting arising from the need for coordination in innovative activities in linked upstream (the GPT) and downstream sectors (the Application Sectors, hereinafter AS). The resulting mutual feedback, that affects the returns on innovative activities both on GPT and AS sectors, has been called dual inducement mechanism, and represents the main feature of the theory at the micro and meso level of analysis. GPTs have then been borrowed by New Growth theory, gaining attention thanks to the book of Helpman (1998).

The main insight from GPT models is, however, a microeconomic one: when sectors are linked in the production and adoption of technologies, the economy is sensible to externalities and multiple equilibria are possible. Given that, and borrowing Greenstein's concise definition, a GPT can be considered in general term as

> a capability whose adaptation to a variety of circumstances raises the marginal returns to inventive activity in each of these circumstances. GPTs are associated with high fixed costs to inventing the technology and low marginal costs to use and reuse. This cost structure both (1) generates heavy early investment — which can occur before and during diffusion of the technology — and (2) leads to frequent repurposing of focal inventions. Rosenberg (. . .) describes this as 'the introduction of a relatively small number of broadly similar production processes to a large number of industries'. (Greenstein, 2010, p. 483)

Literature converges on three main criteria to identify a GPT (In Chapter 2 we label them 'input characteristics'):[1] i) *general applicability*, ii) *technological dynamism*, and iii) *innovational complementarities*, to which one can add some empirical regularities, or output characteristics, that should

[1]With some variance in the terms used and in the number of characteristics listed, see Jovanovic and Rousseau (2005), Lipsey et al. (1998), Bresnahan (2010).

accompany the diffusion of a GPT (Jovanovic and Rousseau, 2005).[2] While the feature of general applicability relates mainly to the technical characteristics of the GPT (that is general purpose because it does 'nothing special', in Simon (1987) words), innovational complementarities are the result of the dual inducement mechanism described above. There, a rise in the 'quality' of the GPT resulting from R&D investments shifts the function of R&D returns also for the AS (in Bresnahan and Trajtenberg (1995)'s formulation, it shifts the AS innovative activities cost function) and vice versa.

The present status of the theory can be condensed in Mokyr (2006)'s claim that — using the past tense — that of GPT was 'a theme that briefly rose to prominence a decade ago in the literature of the economics of technological change', indirectly suggesting the belonging of the concept to a now exhausted wave of economic theorizing. More critically, in his review of Lipsey et al. (2005) book on GPTs and long–term growth, the very nature of GPTs as a theory is questioned: 'The term (GPT) does not (...) constitute a theory. A GPT is in fact a technique that is complementary with a lot of other techniques. How many is a lot the reader must decide, and the nature of the complementarity is left a bit mysterious' (Mokyr, 2006).[3] Our claim is that GPTs can constitute a theory, provided that some clarifications are given. In fact, in addition to the shortcomings just quoted, the GPT framework shows some ex ante as well as ex post definitional problems (see Chapter 2), together with a non–consistent use of the identification criteria outlined above when the theory has been applied to detect GPTs empirically (Field, 2008). The limits of the GPT theory became evident

[2] See Rosenberg and Trajtenberg (2004) for a discussion of the additional feature of 'relaxation of geographical constraints' characterizing a GPT such as the Corliss steam engine.

[3] Mokyr continues questioning the very usefulness of the GPT concept: 'A screw, one would think, is complementary to almost any mechanical construct one can think of, but the screw is not included in their list of GPT. Ships, on the other hand, are. As the authors argue, ships may seem to have only one use (to move objects from A to B) but they qualify as GPTs, as do automobiles, because they can be used to transport almost anything and are thus complementary to nearly any other technique. The same is true for printing, presumably on the argument that almost any kind of information can be printed. But this seems somehow different from, say, electrical power or microprocessors, which are a direct input into the production of many other goods (whereas the printing press only reproduces information). Internal combustion engines do seem rather obvious GPT's, but ships and printing presses only produce one final output, even if that has multiple uses. If the engine and the wheel are GPT's, why not the ball–bearing, the pulley, the lever etc.' (Mokyr, 2006)

in its boom–and–burst application to growth modeling, where it produced nice results however without inducing a follow–up cascade of contributions or establishing a dedicated sub–field of economic theory.

In spite of the relative decline in prominence of GPT studies, recent years have seen a resurgence of the topic, both from a (non–orthodox) macro perspective (Carlaw and Lipsey, 2006, 2011; Rainer and Strohmaier, 2014) and from a micro one (Bresnahan, 2012; Bresnahan and Yin, 2010). New GPT–based growth models enrich the GPT framework including uncertainty and knowledge dynamics among their building blocks, while new micro perspectives extend the basic Industrial Organization framework of dual inducement, studying more in deep the 'Social Increasing Returns to Scale' (Bresnahan, 2010) that GPTs generate, and broadening the framework of analysis. At the same time, the literature has seen a surge in empirical studies related to GPTs (see Section 3.6 for a discussion of GPT empirics). Notwithstanding all its limits, the GPT concept is still fertile.

Given this up–to–date view of GPT theory, the aim of this Chapter is twofold: Firstly, to select the core characteristics of the GPT framework that represent relevant contributions to economic theory, in order to highlight and generalize them. Secondly, to extend this 'core' with additional insights borrowed from the literature on Industrial Dynamics and Evolutionary Economics. As already pointed out in Chapter 2, the macro and historical account of GPTs on the one hand seems to be too much affected by detrimental simplifications; on the other hand, it is 'getting out of hand' (David and Wright, 1999) while transitioning from the theory of the few revolutionary innovations that determine the beginning of 'technological eras', to the theory of multiple and co–existing but simply 'very important' technologies. Therefore, we will focus on a broader concept of GPT: an evolutionary and dynamic process built on micro disequilibria between interconnected industries' incentives to innovate, spillovers and externalities, and economic and technological complementarities.

Our attempt is to frame theoretically the process that drives an initially 'specific' technology, capable of generating positive spillovers in downstream industries' innovative activities, to emerge as a GPT within the network of industrial connections. From a complexity theory viewpoint, the introduction of a GPT induces a differential change in the 'fitness' of the existing technological and economic components of the economic system, modifying their propensity to innovate in a way that is very similar to that captured by the class of 'avalanche' models (Silverberg, 2002) of technological change. Being the result of microeconomic interactions, an (ex post) GPT can be considered as a technological impulse producing as outcome — under certain conditions — a technological multiplier, the latter meaning an acceleration of the rate of innovative activities in related industries. If dual inducements take place, the process generates increasing returns to the use of (investment in) the new technology, with the technology gaining momentum, persistence, and pervasiveness (see Chapter 2), so to become a GPT. In this sense, to understand GPTs as processes, the unit of analysis of the theoretical analysis has to shift from the very GPT to the network of linkages between the potential GPT and its downstream applications. Following the most recent contribution, below we define such network as GPT cluster. Generalizing GPTs to a network phenomenon opens room to a wide range of extensions for the analytical, empirical and policy analyses of pervasive technological change.

The remainder of the Chapter is organized as follows: Section 3.2 provides an assessment of the recent works on GPTs, which have the virtue of isolating the mechanisms leading to the implementation, diffusion, dual inducement and switch between GPTs. Sections 3.3 and 3.4 offer two generalizations of GPT theory: the first establishes a link between GPTs and spillover theories, while the second connects GPTs and unbalanced development theory. Section 3.5 further develops the generalized approach to GPTs, sketching the concept of technological multiplier. Section 3.6 overviews the empirical approaches used in GPT studies and suggests a novel approach consistent with the theoretical claims made in the Chapter. The proposed methodology is used to provide a first illustrive exploration of technological multipliers. Section 3.7 concludes.

3.2 From GPTs to GPT Clusters

In Bresnahan and Trajtenberg (1995), both the GPT and the AS already exist in the economy. The purpose of the model is in fact to highlight the structural connection that ties the incentive to innovate in the two sectors, more than to enquire the nature of GPTs. As the private returns from a technological–level–enhancing innovation in GPT (AS) are also function of the technological level of the AS (GPT), a dual inducement takes place. The number of AS employing the GPT–embodying commodity as an input can increase or decrease (in a sort of diffusion process), depending negatively on the price of the GPT and positively on its quality, where the GPT quality is one of the choice variables whose optimal value results from the condition of equalization of marginal returns and marginal costs of innovating. The marginal returns and marginal costs of innovating are in turn influenced by the R&D investment decisions of the AS. The analysis of the coordination problem that arises due to the (vertical as well as horizontal) externalities generated by this particular structure of interaction is the relevant contribution of that paper.

Recently, Bresnahan provided two studies (Bresnahan, 2012; Bresnahan and Yin, 2010) in order to fill two gaps in the theory, namely: i) which incentives and mechanisms lead to the introduction of a new GPT, and ii) how one GPT is replaced by another. In order to tackle the first issue, Bresnahan (2012) establishes a distinction between different kinds of knowledge and connects such different knowledge types with the likelihood of a technological recombination to take place. More precisely, inventions can be introduced in the market, producing a certain value for their inventors, alone or by raising the returns of other technologies with which they can recombine. However, unless the invention is introduced into the market, nobody knows about it, and possible recombinations are foreseeable only through privately hold entrepreneurial knowledge, which is a characteristic of the inventor himself and of the inventors that have to decide whether to introduce into the market their products with which the first technology can be recombined. If the expected returns for an inventor are high enough to allow the introduction of her invention in the economy, knowledge about it changes its nature from entrepreneurial to distributed market knowledge. Becoming widely available, market knowledge of the innovation influences the behavior of other inventors, modifying their evaluation of the returns of their own inventions and the feasibility of further combinations. A GPT–like invention may not be worth an independent launch into the market, but its likelihood to enter the market can change if other specific-purpose technologies — to be used in combination with the GPT — enter the market, broadening the set of market knowledge.

Depending on the sequence of introduction of the inventions, a GPT can be implemented in three ways: i) as a 'planned initiative', when the GPT comes first and induces complementary innovations; ii) due to 'technological convergence', when special–purpose technologies are invented first — even lacking the knowledge about their potential linkages — creating the conditions for the profitable introduction of a GPT that connects the already existing technologies; iii) due to an 'inversion', when a special–purpose innovation increases the value of inventing a GPT whose introduction, in turn, raises the incentive to introduce a new specific technology. The planned initiative is the classic hierarchical view of the GPT–AS relation, while the processes of technological convergence and inversion shed light on the more imbalanced and circuitous ways through which a GPT enters the economy. These alternative sequences may be useful to describe how some technologies have been introduced in the real world, among them the PC, the E–commerce, the Internet. Besides, the concept of technological convergence — already implicit in Greenstein's definition quoted above — is directly borrowed from Rosenberg (1963)'s historical study of the American Machine tool industry, in which locally emerged technical problems were generalized and solved at an higher level of the production value chain, and the newly produced knowledge was applied to different but related industries (sewing, bicycles, automobiles) using the same small set of widely applicable principles.

The processes of technological convergence and inversion represent GPTs as pervasive technologies in the making, whose success is conditioned on the state of knowledge and on the possibility of recombination. Notably, in none of the stylized cases suggested, a technology starts as 'special purpose' and ends as 'general purpose' — the ultimate GPT is implemented (if implemented) as such, and it does not acquire the status of GPT over time. Also, the 'reuse' of technologies in new combinations — that is, the mechanism through which innovational complementarities take place — is a case of economic complementarity, as it represents the economic viability of additional innovative activities. Technological complementarities are mostly left out of the analysis, even if one can assume that the technological complementarities are accounted for in the value function of an inventor. However, the arguments suggested in Bresnahan's contribution go in the direction of extending GPT theory into a theory of recombinant technologies and linked markets where feedbacks play a fundamental role. Furthermore, the mentioned papers also refer to literature on two–sided markets (Rysman, 2009; Weyl, 2010) because it describes a mechanism of strategic interaction taking place in network industries that is similar to that at the core of GPT–based micro models. This reinforces our claim that GPT theory can be subject to fertile generalizations, useful to increase its explanatory power of phenomena involving linked markets and pervasive technological change.

So far the focus has been on how different GPT–AS structures of interaction allow for recombinant inventive and innovative activities. The other relevant issue to be analyzed has to do with the substitution of one GPT with another. Bresnahan and Yin (2010) emphasize the role that demand plays in determining the switch between GPTs. They extend the classic GPT–AS setting introducing a third layer of interaction, the one of consumers' final demand. This new conceptualization starts from the definition of a set of concentric frames within which a GPT develops. The bigger frame is the 'Broad Technological Opportunity' (hereinafter BTO), a concept related to the well–known notion of technological opportunity (Cohen and Levin, 1989; Klevorick et al., 1995) but meant in a more general fashion. Inside the BTO lies what the authors call a 'GPT Market Cluster', that is the classic coordination game between GPT and AS, augmented by an additional sector: market demand. The economy is thus affected by two contrasting forces: on the one hand, the progressive dual inducement within the GPT and ASs cluster generates increasing returns in the use of the GPTs, and therefore economic growth. On the other hand, as demand changes according to the evolution of consumer needs, the cluster becomes a 'growth bottleneck' for further expansions of the economy. In fact, the GPT cluster, by becoming more coherent, may leave unserved some niches of demand that are outside the cluster. In a sense, the establishment of a dominant GPT drives the system in a lock–in that can endogenously harm the benefits that the GPT itself generated with its diffusion. A new GPT can enter the market serving the unserved demand, therefore relaxing the growth constraint represented by the established GPT. If a new GPT–AS cluster starts to take shape, the increasing returns characterizing also the new technology lead it to serve larger and larger shares of the economy, taking over also ASs served by the older GPT and eventually substituting it. Historical examples of this dynamics are the diffusion of white–collar automation (WCA) and the introduction of personal computing, at the beginning used only to serve the (limited) demand for personal entertainment and, later on, taking over the traditional demand previously served by mainframe and minicomputer architectures.

The discussion of the most recent contributions on GPTs makes clear that GPT studies are shifting back towards a microeconomic approach. The domain of analysis is not anymore that of a few revolutionary technologies. In a more abstract way, the domain of GPTs is that of industries and technologies that trigger responses in linked technologies, markets, consumers niches, and whose pervasiveness is a function of such responses. This change of perspective reinforces the doubts about the appropriateness of the definitional criteria currently used in the literature to describe and identify GPTs. Also, it suggests a change in the unit of analysis. The phenomenon of interest, especially if the ultimate aim is to quantify the potential social and welfare gains, is not anymore the GPT itself. It is the GPT cluster, meant as a system or as a network of technologies, that requires economists' attention. In fact, given that 'it is the joint invention in GPT and many AS which creates economic value' (Bresnahan, 2010, p. 768), the theoretical rationale for a generalized theory of GPTs can be restated as the study on how 'the innovation cost function of a large, heterogeneous economy can be lowered in the aggregate if there is a mechanism to share the fruits of innovative effort across some of these diverse sectors and sub–processes' (Bresnahan, 2010, p. 767). We posit that GPT theory is not about a single GPT, but about linked markets and networked technologies, whose interactions in economic and innovation activities lead to the establishment of pervasive (upstream) technologies, and eventually to their replacement.

3.3 A First Generalization: GPTs and Spillovers

The concepts discussed in the previous Section help to define the boundaries of a Microeconomics of GPTs or, more generally, a Microeconomics of heterogeneous technological change. In fact, the collection of tools outlined in order to generalize GPTs includes the dual inducement mechanism and externalities, the alternative processes for the establishment of a GPT, the concept of GPT cluster, and the role demand plays in facilitating GPTs substitution. This collection can be further extended by adding arguments that capture the additional features of the dynamics of GPTs. In Chapter 2 we outlined how theoretical building blocks borrowed from Industrial Dynamics literature (dynamic economies of scale, network effects, dominant designs, competition between technologies, collective invention) describe patterns that are similar to those leading to the persistence and pervasiveness[4] of GPTs and their related clusters. However, one has to keep in mind how the theory of GPT in its main contributions is mainly a theory concerned about linked innovative activities, where the choice variable is the magnitude or the change in R&D expenditures or similar innovation input and output. This restricted perspective has already been partially broadened in the discussion done so far, but it is important to remember the distinction between economic and technological effects related to GPTs.

In this Section we further elaborate on the extensions of the GPT framework, connecting GPTs and the literature on spillovers. Previously, we claimed that what matters for the emergence of a GPT are not only some characteristics of the technology itself, but the cascade of inducements to innovative activities it produces, that is the network of interdependencies between user and producer industries. GPTs are *enabling* (Bresnahan, 2002), in the sense that they raise the expected returns of investments in innovative activities,

[4]For definitional purposes, the use of terms prevalence, persistence, and pervasiveness has to be defined more precisely. Prevalence refers to a technology that represents the established (if unique) choice for a given function or task to be performed, and it is usually the final outcome of a competing technology dynamics (Arthur, 1989). Persistence relates prevalence to the time dimension, so to its continuation over time. Finally, the pervasiveness of a technology depends on its patterns of diffusion, adoption and use, so to its spread across the set of economic activities. A technology may be prevalent in a single application sector but irrelevant in others or show — using GPT criteria — general applicability, so a cross–industry ease of application that makes it pervasive.

and this feature — not shared by other technology–related concepts — give them a special status among technologies. The role of an enabling technology is to refresh technological opportunities. Given that, in general, R&D expenditures are subject to decreasing returns due to the convexity of the set of technological opportunities, the interaction with an enabling technology produces additionality — that is a positive externality, or a spillover.[5] As Wright puts it,

> (. . .) at any point in time a number of more fundamentally innovative ideas may be spreading through the economy, typically without explicit public or private sponsorship, their potential as yet incompletely realised in practice. This is another broad lesson (. . .): No matter how successful we may be in accounting for purposeful investments in the generation of knowledge, the historical record persistently reflects the impact of forces that are not readily accounted for in this way, something like 'technological opportunities' which we may describe (eschewing the now–forbidden term 'exogenous') as having historical trajectories of their own (. . .). The extent of technological opportunity for a particular sector is related to its proximity to what are known as 'general purpose technologies' (. . .). (Wright, 1997, p. 1561)

GPTs can be considered as sources — and products, if one considers dual inducements — of spillovers. They shift — through their use as an input in the downstream sectors' innovative activities and production processes — an AS's curve of returns from innovations for a given level of R&D intensity which, in turn, approximates the size and extent of technological opportunities. Carlaw and Lipsey (2002) are the only scholars who explicitly theorized the relation existing between GPTs and spillovers. In order to shed some light on this relation, they defined the concept of technological complementarity: 'a technological complementarity arises in any situation in which the

[5] From an alternative perspective, the 'refreshing' of opportunities can be seen as a reduction of uncertainty. Concerning the theoretical distinction between externalities and spillovers, see Mokyr (2006). In this text, however, we use them as synonyms. Furthermore, one can discuss different types of spillover such as knowledge or pecuniary ones (Griliches, 1979; Verspagen, 1997).

past or present decisions of the initiating agents with respect to their own technologies affect the value of the receiving agents' existing technologies and/or their opportunities for making further technological changes.' (Carlaw and Lipsey, 2002) Technological complementarity is a special case of dynamic externalities (spillovers), because it does not necessarily produce a shift in related sectors' production functions, but it changes the whole logic through which inputs are used. This definition goes hand in hand with the concept of enabling technology: the effect of a GPT is not just a change in techniques, but a widening of opportunities. However, to the author's knowledge, no theoretical bridge exists between specific R&D–cum–spillover studies and GPTs.

The part of Industrial Organization literature that is devoted to spillovers models the entire spectrum of possible cases, ranging from intra–industry or horizontal spillovers (d'Aspremont and Jacquemin, 1988) to inter–industry or vertical ones. The latter possibility has been studied in the case of vertical spillovers coming from the upstream industry (Harhoff, 1996) as well as in the opposite direction, where externalities in downstream R&D expenditure raise input costs, partially offsetting the returns to innovative activities but also producing a rise in (non–innovative) rivals costs (Banerjee and Lin, 2003). In these contributions, the study of vertical spillover is never meant to focus on the simultaneous presence of the inducements in both directions. In fact, in vertically related industries, a case can be made for the presence of a crowding–out effect, where downstream R&D expenditures are substituted by external (upstream) ones. Producers of final goods, for example, reduce their inventive efforts since they benefit from suppliers R&D in terms of know–how embodied in their inputs (knowledge spillovers) or as non–complete adjustment of prices to quality advancements (the so–called rent spillovers — see Griliches (1979)). Only the model of Harhoff (1996) describes an exception to this expected negative spillover effect. There, a generic R&D activity that is common to all the firms — and that is negatively affected by marginal increases in upstream investments — is coupled with a specific kind of R&D that reflects idiosyncratic and firm–specific knowledge and capabilities, and is positively influenced by a vertical spillover. Upstream R&D expenditures induce the re–allocation of downstream resources to specific–knowledge investments, with the result of increasing innovative activities. The complementarity nature of knowledge spillovers is modeled only in the case of intra–industry spillovers, for example in the model of Levin and Reiss (1984). There, firms' R&D intensity is function of the elasticity if the industry knowledge pool to a firm investment. According to the value taken by the elasticity, R&D investments by competitors can produce either crowding–in or crowding–out. However, vertical relations between different industries are not taken into consideration.

Contrariwise, empirical research found traces of positive inducements. However, studies focused mainly on the estimation of the signs and magnitudes of vertical spillovers not on R&D intensities, but on productivity measures such as total factor productivity. In particular, since the studies of Scherer (1982) featuring technology–flow analysis, many scholars (Wolff and Nadiri, 1993; Verspagen, 1997) measured the relevance of inter–industry technology spillovers, finding that an industry rate of technological progress is significantly (and positively) related to that of its suppliers. The main problem of this kind of analysis is that the vertical spillover may not leave a trace in performance indicators if the inducement produces only a change in the direction of innovative activities, and not in its rate, or if the effects appear with very long time lags (Carlaw and Lipsey, 2002). These possibilities are implicit in the enabling nature of GPTs, and represent a challenge for empirical analysis.

In sum, the literature on spillovers fails to take into account the dimensions of feedbacks and technological complementarities that are instead features of GPTs. With regards to vertical spillovers, that is the case matching closely the GPT–AS interaction structure: On the one hand, theoretical models focus on inducements on R&D expenditures as a choice variable but do not capture the possibility for positive and dual inducements. On the other hand, the empirical literature successfully identifies positive spillovers; however, it does that relating upstream technological change to downstream economic performance, and this biases an analysis of the enabling effect of a potential GPT on technological opportunities.

This paragraph suggested a first generalization of GPT theory, that we now summarize in the following sentence:

GPTs, meant as a networked phenomenon, can be considered a special case of spillovers, namely inter–industry (vertical) spillovers involving enabling technologies and technological complementarity.

3.4 A Second Generalization: GPTs and Unbalanced Development, or 'Schumpeter meeting Hirschman'

Our discussion so far suggests that GPTs are sources of very specific positive spillovers, involving the enabling of further technological opportunities for downstream and user sectors. Another direction to be explored to extend GPTs to a more general networked view of heterogeneous technological change is that of the type of process leading to the establishment of a GPT. Bresnahan and Yin (2010) emphasizes the role of heterogeneous demand and unserved demand as the key to break growth bottlenecks and switch from one GPT to another. In a view that focuses less on the single GPT and more on the succession of steps leading to the prevalence and pervasiveness of a certain sector or technology, here we suggest that another explanatory route to take is that to consider the establishment of a GPT as an unbalanced (asynchronous) process, that is a special case of unbalanced development theory.

Evolutionary and Neo–Schumpeterian economists build their models and theories on population thinking and on an out–of–equilibrium view of the economic system; heterogeneous and differential growth is therefore implicitly assumed as a driver of economic change and 'retardation' dynamics (Metcalfe, 2003). This view was however already conceptualized in the Fifties by Albert Hirschman. In the midst of a long–standing debate between supporters and contenders of the Big Push theory in Development economics, he suggested that it is the continuous tension between backward and forward industrial linkages that generates dependencies, disequilibria and therefore, unbalanced growth (Hirschman, 1958).[6] The very existence

[6]See Alacevich (2011) for a historical account of the debate and the description of the divides along which early development economics was split, and Murphy et al. (1989) for

of linked markets and their differential evolution over time creates at the same time inducements and bottlenecks that, when relaxed, open room for industrialization and growth. In this context, 'leading sectors' are the core and drivers of the process of unbalanced growth. A similar process is at work within a GPT cluster. As Bresnahan and Yin (2010) suggest, the establishment of more GPT–AS linkages generates at the same time increasing returns (growth) and demand bottlenecks that harm growth on the long run. Therefore, we suggest that the basic GPT model can be considered as a special case of unbalanced change, with two caveats: First, in the GPT case the unbalanced development is related not to economic growth, but to incentives and constraints to technical advance and innovative activities; Second, the structure of interaction characterizing a GPT cluster is very specific, as the linkages take the shape of a star (Carvalho, 2014), or a tree, with a single backward 'node' with multiple forward connections.

It is within this tree–like structure that vertical and horizontal externalities occur. In fact, the introduction of a new specific purpose technology in an upstream market affects the innovative behavior of the downstream industries. The linkages work as bottlenecks and channels for forced interaction that, in turn, shape the opportunities for further innovative activities. The imbalance created by the spillovers from upstream is asynchronous, in the sense that not all the linked downstream application sectors respond in the same way, and with the same timing, to the upstream spillovers. The outcome of this differential response determines the state of the system from period to period, and shapes the conditions for successive waves of innovation activities, in an uneven cascade of effects.

Provided that the fundamental mechanism at work in a GPT cluster can be meant as a special case of unbalanced development, we can use this insight to investigate the process leading to the substitution between old and new GPTs. We refer again to the idea of growth bottlenecks suggested by Bresnahan and Yin (2010). Growth bottlenecks are the 'points of resistance' slowing down the unbalanced process of inducement taking place in a GPT cluster and can be distinguished in two categories. On the one hand, we have the feature of a GPT to relax what we call an economic bottleneck, that

a formalization of Rosenstein–Rodan's Big Push theory.

is, to satisfy unserved demand. Economic bottlenecks are related to market conditions and consumer preferences. On the other hand, new technologies with the potential to become GPTs are often introduced as a response to a technical challenge, or reverse salient (Sahal, 1985). These technologies are the outcome of problem–solving activities (Arthur, 2009) and are the key for the process of technological convergence (Rosenberg, 1963). In this case, we face a technological bottleneck. The role played by technological bottlenecks is broader and not only confined to the incentives to introduce a GPT. The adoption/diffusion process within a GPT cluster can be slowed down or stopped due to the presence of a technological bottleneck. Once this is removed, GPT–like innovations get often adopted at a very fast pace (Goldfarb, 2005). In fact, as Goldfarb (2005) points out in the case of the diffusion of electrification in urban mobility, printing and paper production sectors, technological bottlenecks appearing at the GPT level affect adoption rates in a significative way, as compared to other factors shaping diffusion patterns such as input and labor costs, sunk costs of existing equipment and capital structure, and co–invention costs occurring at the application sector level.

The idea of an asynchronous evolution of the economy is not confined to Hirschman's insights during the 'years of high development theory' (Krugman, 1992). It is indeed a fundamental building block of recent contributions on adaptive growth modeling (Metcalfe et al., 2006) and on avalanche models of technological change (Silverberg, 2002). However, such approaches do not perfectly capture the specific nature of inducements and linked payoffs within and between GPT clusters. The first case describes industries' disequilibrium dynamics relying on a mix of evolutionary and Kaldorian analytical tools (namely, the replicator dynamics model augmented by technical progress functions explaining increasing returns and investment rates). This approach tends to embody technology dynamics into changes in labor productivity and labor requirements. Models in this tradition capture dynamic externalities but may fail to represent technological complementarities induced by enabling technologies. The second strand of literature explains the percolation phenomenon leading to cascades of innovations using analytical tools borrowed from complexity theory. A percolation or avalanche model assumes heterogeneity in adopters' propensities to accept a new technology, and this feature captures the unbalanced nature of inducements we discussed so far. However, these models pay the price of an abstraction from the real working of the economic system, and are therefore not easy to operationalize for empirical purposes. Another concept related to the dynamics of a GPT cluster is that of development block (Dahmén, 1988). Development blocks are used to describe a dynamics of industrial transformation close to that outlined in this Chapter with regards to GPTs. In particular, by conceptualizing a development block as the unit of analysis for the study of technological and industrial change, Dahmén emphasizes the role played by complementarities in generating structural tensions, or disequilibria. The interactions of several structural tensions 'may result in a balanced situation' (Dahmén, 1988, p. 5). Structural tensions and (economic and technological) bottlenecks both drive and channel unbalanced development processes. In this sense, a GPT cluster can be defined as a development block with the capability to affect a large share of the economic system.

As we claimed in the previous paragraphs, the establishment of a GPT can result from an unbalanced process of inducement of innovative activities and positive feedbacks between linked markets and technologies. Particular attention should be devoted to the types of deviations from balanced paths that the establishment of a GPT generates. The effect of GPTs on the rate and pace of technological change is unbalanced because they rejuvenate existing opportunities and enable new ones in downstream industries, and this effect unevenly propagates through the economy. Given the general applicability feature of GPTs, their innovative impulse is quickly transmitted to the whole industrial network of interdependencies. Here, the initial state and structure of the system matter: if R&D returns in different industries are aligned on a similar level, the introduction of a GPT like impulse could generate even or uneven inducements to innovative activities according to the industries' specific reactions to the new enabling technology. Similarly to Levin and Reiss (1984), the different reactions can be thought as elasticities of industries' R&D intensity to the R&D intensity of the GPT industry. The opposite situation can also hold: if R&D returns in different industries are not aligned on the same level, then the differential push to innovative activities provided by the new technology may produce a re–alignment (synchronization) of the economy–wide rate of innovative activities.

The distinction made here resembles the one suggested by Harberger (1998) — and then used by David and Wright (1999) to explain Solow productivity paradox and the rapid U.S. productivity acceleration during the Twenties due to electrification — between yeast and mushrooms–like growth processes. Again, there the focus is economic performance (productivity) instead of innovation performance, but the concept should be kept in mind as a useful guide to help to detect the process of GPTs' establishment: while localized technical change (Antonelli, 1996) is economically and geographically bounded as mushrooms growing up (whose emergence do not structurally affect the 'ecology' of the system in which they appear), generic processes of technological reconfiguration affect the whole set of economic activities at the same moment, as growing yeast expands in all the directions at each point in time. The latter process better captures what happened in the case of electrification–driven productivity advances, which were spread and shared by the whole set of industries in the manufacturing sector (David and Wright, 1999). The nature of the diffusion process — more mushroom– or yeast–like — depends on the degree of heterogeneity of the spillover–receivers (the downstream industries) in terms of technological opportunities and readiness to adopt a new upstream technology. In short, the distribution of characteristics in the downstream market sets the stage for the dynamic formation of a GPT cluster.

In any case, a yeast–like balanced process and a mushroom–like unbalanced process of technological change are not at odds with each other. The yeast–like expansion of the economy is in fact an ex post outcome. The generating process behind such homogeneous outcome can be an impulse intervening on a heterogeneous distribution of propensities to react to generic technological change. In its case study of electrification in three U.S. sectors, Goldfarb (2005) already develops the idea that even a process usually recognized as yeast–like (David and Wright, 1999) is in fact subject to a much less homogeneous dynamics than usually thought. In that case, technological bottlenecks affecting the GPT development determined the different rates of diffusion of the electric dynamo across industrial sectors, that persistently showed a non–negligible dispersion until at least the beginning of the Thirties. Napoletano et al. (2006) show in a model how, in a multi–industry economy that accounts for cross–industry elasticities to productivity shocks, total factor productivity growth can result from a 'purely idiosyncratic' shock, from a 'pure GPT' process, or from linear combinations of the two. As a results, 'the GPT model can only produce a smooth cross–sectoral growth pattern if the elasticities of sectoral TFP to shocks from other sectors are similar across sectors. On the contrary, under heterogeneity of elasticities, growth asymmetries can be observed even if a common component drives the productivity growth of all industries.' (Napoletano et al., 2006) In a nutshell, this means that evidence of a GPT cluster formation should not be inferred only from synchronous cross–industry transformations. Under the condition of heterogeneous elasticities of industries' performance to external shocks, a GPT–process can be at work despite the evidence of mushroom–like outcomes. This happens because the heterogeneity of responses to a GPT–like inducement, meaning the particular shape of the distribution of returns to adopt/use a potential GPT, works like a filter that transforms balanced in unbalanced change, and vice versa. From an empirical perspective, the difficulty to disentangle a GPT–process in the making from its market outcomes renders the identification of GPT clusters problematic, as it is discussed in Section 3.6.

Furthermore, what matters in the unbalanced development of GPT clusters is also the speed of the process: if potential GPTs — as we briefly suggested in Section 3.3 — are able to generate dynamic economies of scale or, in Bresnahan (2010) terms, to lower the cost function of a whole heterogeneous economy, then the unbalanced inducement process will be faster or more intense, leading to a generalized expansion of the economy. This is, of course, not a necessary condition: long lags can show up between the introduction of a potential GPT and its realized effects on the economy, which is the very essence of the Solow paradox. However, this is what we would define in other contexts as an 'emergent property' of a complex system: many feedback interactions at a micro level leading — mostly in unforeseeable ways — to a tipping point, showing 'broken symmetry' (Anderson, 1972) and macroscopic consequences.

This paragraph suggested a second generalization of GPT theory. We summarize it in the following sentence:

In its dynamics, a GPT cluster is a special case of unbalanced development, with a peculiar structure of interaction, and focused on cascades of effects on innovative activities rather than economic performance. The enabling nature of technological complementarities and spillovers, the feedbacks taking place within the GPT cluster, and the heterogeneous distribution of responses to these inducement effects can result in a synchronous or in an asynchronous change.

3.5 Toward a Theory of Technological Multipliers

So far, we outlined a conceptualization of GPTs and GPT clusters as special cases of spillover theories and unbalanced development theories. In what follows we proceed in our construction of an extended theory of GPT, suggesting that the concept of technological multiplier provides a nice description of the process leading to the emergence and establishment of a GPT cluster.

In a critical discussion of Long Waves theory, Rosenberg and Frischtak (1983) claim that — in order to be able to support the hypothesis of causality running from innovation (mainly a micro phenomenon) to historically relevant fluctuations (a macro phenomenon) — one should assess whether such hypothesis is compatible with a series of conditions regarding *causality* itself, *timing*, *economy–wide repercussions* and *recurrence* of technological innovation. Fulfilled such conditions, one would be able to clearly qualify technology as *primum movens* of Long Waves, and to reject the alternative hypothesis according to which innovations are 'disciplined and structured' by long term movements. This discussion summarizes the two main lines of research that deal with the issues already identified in Schumpeter's Business Cycles (Schumpeter, 1939): the identification of Long Waves (Silverberg, 2003) and clustering of innovation (Silverberg and Verspagen, 2003). The same arguments serve as a yardstick for our extended theory of GPTs. In fact, a GPT cluster and a cluster of radical innovations share a similar characteristic: they occupy a 'strategic position in the economy in terms of backward and forward links' (Rosenberg and Frischtak, 1983).

On the analytical side, to take on board this view means that the modeling of GPT clusters has first of all to be grounded on the micro and meso level of analysis. In such a model an initial localized pulsation (a new upstream product from existing industries, or the birth of a new upstream industry) enables a wave of forward and backward innovation expenditures as well as positive feedbacks on the locus of the originating ‘push’. Forces playing against positive feedbacks, for example the resistance of existing technologies and the threat of competing technologies, crowding–out effects on innovation incentives generated by other sources of externalities, adverse conditions in terms of macro–prices and expected profits, can contrast the enabling potential of a technology. In this case, a candidate GPT fails to become a GPT, a possibility currently featured only in the model of van Zon et al. (2003). If instead the enabling feedback mechanism prevails, dynamic economies of scale kick–in, and a technology suited to be specific becomes general purpose.

If we are ready to borrow concepts from other strands of literature, we can define our generalized approach to GPTs as a fully–fledged *technological multiplier*. In the Keynesian view of fiscal multipliers, public expenditures boost growth via a progressive cascade of increases in consumption and investments (directly affecting, together with expectations, the marginal efficiency of capital). In the same manner a GPT–based inducement effect can generate a wave of additional growth (a crowding–in effect) in downstream industries’ innovative activities. As the effect of the fiscal multiplier can be decreased by the pre–emptive anticipative actions of agents endowed with rational expectations, the potential of the technological multiplier can be depressed by the forces contrasting enabling positive feedbacks. As the fiscal multiplier models the potential cascade of economic consequences from an initial expenditure impulse, the technological multiplier captures the percolation of positive feedbacks through the network of industrial linkages started by an initial technological impulse. The point of origin of the multiplier impulse can benefit from returning positive feedbacks, therefore further increasing its performance. By improving its attractiveness for additional applications and linkages, it gains pervasiveness and begins the formation of a GPT cluster.

To follow empirically the traces left by a technological multiplier may turn to be a non–trivial exercise, as suggested later in Section 3.6. In any case, the detection of a technological multiplier at work can represent a new criterion to identify the process of formation of a GPT cluster, and thus the pervasiveness in the making of technologies and sectors that might drastically affect the whole economy. The idea that a multiplier mechanism is at work in the domain of innovative activities can be found in Dietzenbacher and Los (2002). They studied R&D multipliers using inter-industry flows of embodied R&D and distinguishing between backward and forward multipliers, however without an explicit reference to GPTs. A classic contribution by Momigliano and Siniscalco (2013) go as well in the direction to identify the transmission of technological know–how through production blocks (vertically–integrated sectors) rather than through standard economic branches. Also Eliasson (2011) develops the similar concept of 'spillover multiplier' and studies the channels easing the multiplier effect in the context of the Swedish military aircraft industry.

An additional consideration to be made for prospective modeling exercises in the direction suggested by this Chapter regards to the role played by technological complementarities. It is important to stress this point further, since it is one of the missing links in the received microeconomics of GPTs described in Section 3.2. In Bresnahan and Trajtenberg (1995)'s definition, GPTs spawn innovational complementarities, a notion that in the model is interpreted in purely economic terms: technical advance is the result of growing returns and profitability, which in turn are properties of the mutual feedback structure of the GPT–AS coordination game. The concept of technological complementarity, to be understood as the structure of interdependencies and compatibilities between the components of a technology meant as a system of parts, where such components are technological systems themselves, in a recursive way, and are arranged in a modular, hierarchical or near–decomposable architecture (Arthur, 2009), is not part of the analysis. However, technological complementarity is one of the determinants that affect the dynamics towards prevalence, persistence and pervasiveness of a given technology, because it influences the reach of technological exploration and exploitation and determines the feasibility of certain designs, technological recombinations and improvements within the fitness landscape (Frenken, 2006). Moreover, technological complementarity produces micro as well as meso/macroeconomic effects, where learning is an example at the microeconomic level, while investments in complementary capital and their effects on real output, wages, and productivity are examples at the macroeconomic level.

In fact, the allocation of resources to make old and new technologies 'tailor–made' for each other (Aghion and Howitt, 1998) and, therefore, the magnitude of the conversion costs, as discussed by Arthur (2009) for the process of technological re–switching, could be one of the factors influencing the sign of the downstream response to upstream spillovers, and one of the explanatory variables solving the paradox of the lagged effects of new paradigmatic technologies on productivity (Solow, 1987). The issue of technological complementarity is partially tackled in the growth model of Helpman and Trajtenberg (1994), where the main mechanism leading to the so–called 'time to sow and time to reap' fluctuation dynamics, relies on the fact that a new GPT cannot be used until a set of components that are specifically tailored for that technology have been developed by devoting R&D resources to this activity. In that model, GPT–specific — that is, technologically complementary — components are usually produced with a CES production function. This assumption makes components proportionally substitutes, therefore relaxing a strict interpretation of technological complementarity meant as architectural compatibility and compositional dependence (Lombardi, 2010). To consider technological and economic complementarities together is therefore an important criterium to follow in order to model GPT clusters and technological multipliers.

This paragraph suggested a further refinement of GPT conceptualization. We summarize as follows:

An extended theory of GPTs and GPT clusters is in a more general way a theory of technological multipliers, in which an enabling technology affects the sectors to which it is linked, and it is affected by them. The net effect resulting from positive feedbacks, driven by economic and technological complementarity, and negative feedbacks determines if the technology or the sector under consideration succeeds to gain pervasiveness, to establish a GPT *cluster and eventually to influence the direction of an economy's evolution.*

3.6 The Empirics of GPTs and Technological Multipliers

Once the theory of GPTs has been extended to that of GPT clusters and further to that of technological multipliers, the possibilities for empirics of GPTs can be assessed. Existing empirical analysis of GPTs follows four main directions: the first *assumes* a technology to be a GPT, and studies its aggregate effects on the economy. In this framework, studies mostly focus on assessing the contribution of ICT to delayed productivity growth (Basu and Fernald, 2007). The second approach *presumes* a technology to be a GPT, and focuses then on detecting some output characteristics, regularities, or stylized facts derived from theoretical expectations and related empirical insights (Jovanovic and Rousseau, 2005). A third direction narrows down the scope of analysis, producing *case studies* about the general applicability and diffusion of certain technologies, such as the Cohen–Boyer rDNA technology, electrification in specific industries or nanotechnologies (Feldman and Yoon, 2012; Goldfarb, 2005; Youtie et al., 2008). Finally, a fourth more comprehensive approach is the one pioneered by Hall and Trajtenberg (2004) which, using *patent data*, attempts to detect GPTs selecting a sample of technologies ranking at the top in a set of indices created to proxy the three GPT input characteristics: general applicability, dynamism and innovational complementarities. Further studies exploit patent data to study the effect of policy interventions — in particular, innovative public procurement — on the generality of focal inventions (Raiteri, 2015) or assess how the adoption of GPT–like 'Key Enabling Technologies' enables the formation of new European regional technological advantages (Montresor and Quatraro, 2015).[7] Even if carefully performed, such empirical exercises are by definition suffering from the shortcomings of patent data. Patents,

[7]Key Enabling Technologies are those identified by the European Commission in its 2009 Communication 'Preparing for our future: Developing a common strategy for key enabling technologies in the EU' based on their economic potential, contribution to tackle societal challenges, and knowledge intensity. They are: i) Nanotechnology, ii) Micro– and nanoelectronics, iii) Photonics, iv) Advanced materials, v) Biotechnology, and vi) Advanced manufacturing systems.

in fact, do not capture the whole extent of inventive activities and are subject to data truncation. Data truncation, in the case of GPT empirics, represents an even more severe limitation given that the identification of new or potential GPTs requires up to date citations and does not permit to fully explore the length of citation lags. A different empirical approach, not directly developed within the GPT framework, is the one introduced by Kaplan and Vakili (2012), which runs topic detection algorithms on patents abstracts in order to isolate theoretical breakthroughs starting from their very conceptualization.

Alternatively, an empirical analysis of GPT clusters can be designed around the theoretical building blocks developed so far, exploiting information from spillovers and industrial linkages. The already cited quantification of the externalities of R&D expenditures generating R&D multipliers (Dietzenbacher and Los, 2002) is one of the few studies that delve into these dimensions. As a possible empirical strategy, one could assess parametrically the presence of positive spillovers on R&D expenditures, testing the existence of a technological multiplier against the expected signs of the spillover effect, given the position of an industry in the Pavitt classification. The taxonomy developed by Pavitt (1984) arranges the diversity of technical change by classifying firms (industries) in science–based, specialized suppliers, intensive production, and supplier dominated.[8] Pavitt taxonomy offers an elaborated picture of industries in terms of the sources of technical knowledge and spillovers, and presents a rough hierarchy of linkages between the types of industries; such hierarchy of linkages gives an idea of the direction of the innovative spillovers (Pavitt, 1984, p. 364). Controlling for parameters that are usually affecting the level of R&D expenditures such as technological opportunities (Cohen, 2010; Klevorick et al., 1995), demand conditions, the regime in which innovative activities occur (Malerba and Orsenigo, 1997), firms' size (which, despite the limits of the so–called Schumpeterian hypothesis, still maintain some power to explain R&D intensities, mainly through a cost–spreading argument (Cohen and Klepper, 1996)), investments to develop absorptive capacity (Cohen and Levinthal, 1989), and industries' market structures, the residual presence of an inducement mechanism may be iden-

[8] For extensions of the taxonomy including information–processing industries and the service sector see Archibugi (2001) and Castellacci (2008).

tified. Such inducement can provide supporting evidence in favor of a GPT cluster formation, especially if found in those industries that are expected to respond negatively to spillovers, for example supplier dominated industries such as textile. In these cases, a detected generalized positive propensity to increase innovative expenditures could uncover innovational complementarities and a GPT in the making.[9] However, the limits highlighted by Napoletano et al. (2006) still apply: the data generating process behind positive inducements can be a pure idiosyncratic process, a pure GPT process, or a combination of the two.

As an alternative, we briefly suggest here a non–parametric methodology to trace the establishment of GPT clusters. The idea is to capture the broad effect of technological multipliers focusing on R&D accelerations, where acceleration is meant as a proxy for innovation inducement and, hence, for the multiplier effect. The variable measuring R&D acceleration is the growth rate of R&D expenditures. The GPT cluster in the making is studied only indirectly, refraining from the attempt to identify the single perfect candidate technology for the role of GPT. Given the difficulty to disentagle the sources of the technological multiplier, we shift the focus of the analysis to the changing dispersion of R&D acceleration, that is on the distributional properties of innovation inducements. Sapio and Thoma (2006) and Castaldi and Sapio (2009) study the distributional properties of sectoral growth rates to gain insights into the identification problem pointed out by Napoletano et al. (2006). We apply the same methodology to sectoral R&D expenditures growth rates instead of sectoral growth rates of value of shipment or value added.

We use OECD STAN Research and Development Expenditure in Industry (ISIC Rev. 2) for the United States in the period 1973–1997, and restrict the analysis to 24 Manufacturing industries. The choosen database has the

[9] A parallel claim can be made concerning the intra–industry incentive to invest in absorptive capacity. In presence of positive spillovers, despite an incentive to exploit others' R&D investments leading to a reduction in R&D intensities, the opposite tendency is often found, driven not by GPT–like inducement and innovational complementarities, but by the strategic choice to improve the capabilities to understand and use external knowledge. This 'second face' of R&D expenditures provides a hypothesis of inducements that produces similar effects to the GPT one suggested in this Chapter, opening room for empirical analysis and comparisons.

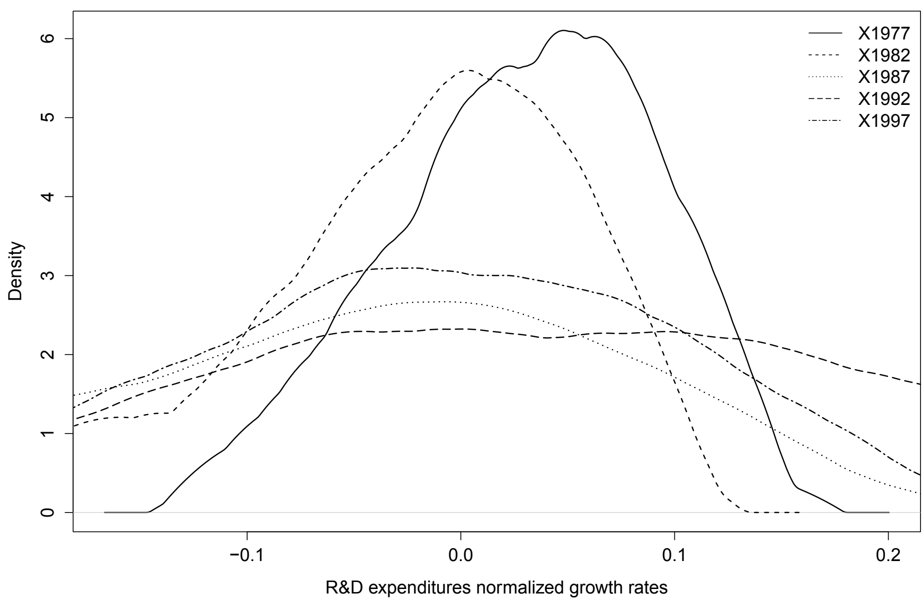

Figure 3.1: Kernel Density of five years R&D expenditures growth rates for 24 Manufacturing industries — 1973–1997

limit to leave out the last two decades of ICTs diffusion, but allows for a time span long enough to permit more period–to–period comparisons. Following Castaldi and Sapio (2009) the variables used are the normalized logarithmic R&D expenditures, calculated as $r_{i,t} = \log R_{i,t} - \log < R_{it} >_t$, where $r_{i,t}$ indicates the normalized value of R&D expenditures for industry i at time t, capital letters represent non–normalized values and $< . >_t$ is an average at time t across the industries. The annual growth rate is then calculated as $g_{it} = r_{i,t} - r_{i,t-1}$. To reduce the effect of random shocks potentially occurring in particular years, we take a 5–years growth rate ($g5_{it} = r_{i,t} - r_{i,t-5}$) as unit of analysis. Figure 3.1 shows the Kernel density estimation of the 5–years R&D expenditures growth rates:

The general pattern of R&D accelerations as shown by the dynamics of the distributions suggests a tendency to de–concentration of industrial R&D growth rates, at least in the first three periods of analysis. An increase in the heterogeneity of R&D growth rates may reflect the differential magnitude of the technological multiplier effect, potentially driven by a common component. The last period is characterized by more industries experiencing an R&D growth acceleration, with the right tail of the distribution becoming fatter. This latter tendency may be related to the reaction of several industries to the technological opportunities provided by the GPT cluster related to ICT and informational platforms, that became fully exploitable after a discovery and learning lag.

Using additional STAN data (Research and Development Expenditure in Industry, ISIC Rev. 4), we can explore the distributional shapes of R&D expenditures growth rates in more recent periods. The same exercise is repeated with a more fine–grained dataset (35 industries, including services), using a 5–year growth rate (Figure 3.2) and a 2–year growth rate (Figure 3.3) for the period 2002–2012. The acceleration of innovative activities seems to become more uniform during the last period of analysis, with growth rates showing a higher concentration. Figure 3.2 illustrates — using shorter time periods as the reference to calculate growth rates in industries' R&D expenditures — the tendency of growth rates to shift from being more to less heterogeneous. Combining the evidence from the different periods, the broad picture that emerges from this illustrative exercise is one of continuous change in R&D accelerations. The dynamics of R&D growth across industries seems to oscillate from homogeneity to heterogeneity (meaning by more spread distributions), and once again to homogeneity.

The dynamics of R&D acceleration may provide additional insights into the functioning of the process behind industries' technological innovation. In line with Napoletano et al. (2006), pure idiosyncratic and pure GPT processes cannot be unambiguously identified, and therefore not much can be claimed about the generating process behind R&D inducements. However, this exploratory analysis already uncovers a generalized tendency of industries to behave alternatively in a yeast– or mushroom–like way in their innovative activities. A deeper historical analysis and a more refined study into the lags of adoption and formation of certain GPT–clusters may complement this kind of preliminary evidence.

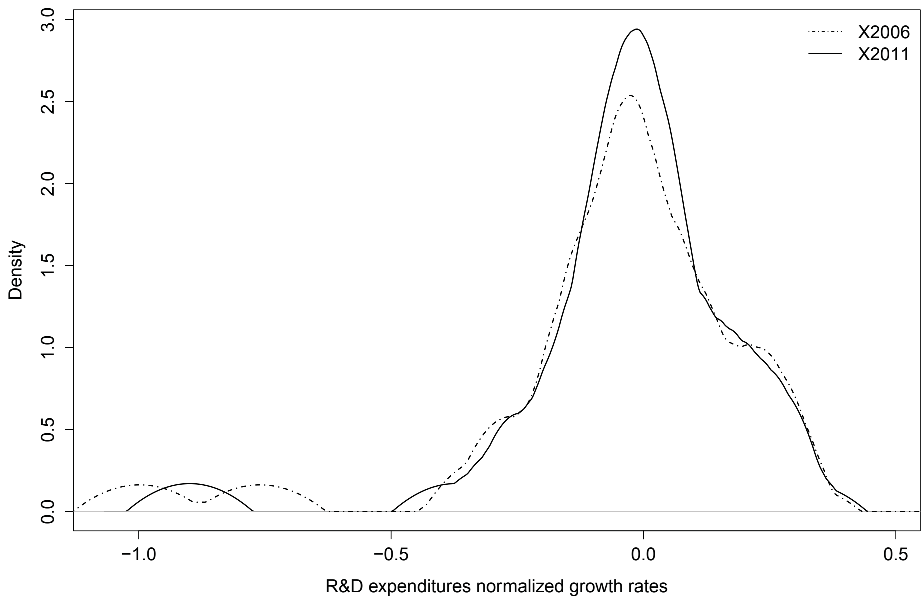

Figure 3.2: Kernel Density of five years R&D expenditures growth rates for 35 industries — 2002–2012

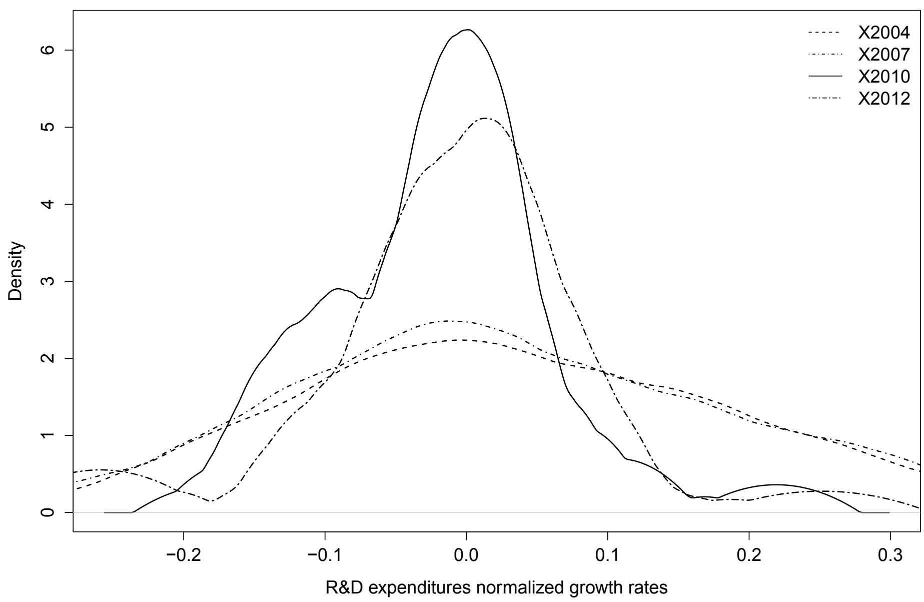

Figure 3.3: Kernel Density of three years R&D expenditures growth rates for 35 industries — 2002–2012

3.7 Conclusion

In this Chapter we suggested three directions to generalize the theory of GPTs. They all share the idea that GPTs have to be considered as network phenomena. The unit of analysis should not be a single, discrete, and radical technological innovation, but the GPT cluster and the technological multiplier effect that the establishment of a GPT kicks–in. The basic building blocks employed in the classic GPT models have been complemented by concepts developed in the fields of Industrial Organization, Industrial Dynamics and Development Economics. A case is made for framing the theory of GPTs as special cases of spillover theory that deals with enabling technologies, and of unbalanced development theory. Eventually, GPT theory is extended to a theory of technological multipliers, that is a theory of innovative activities in linked markets, where feedbacks play a fundamental role in determining the outcomes of the system under analysis.

The proposed theoretical framework is supposed to inspire new research questions and applications for GPT theory. Possible research paths are the critical reprise of theories of long–run technological change and Long Waves, and the merging of complexity models with microeconomic building blocks in order to explain part of the non–trivial (and most probably non–linear) dynamics produced by technological change in a network of linked industries. Also the study of industries' statistical regularities (Cohen and Klepper, 1992; Dosi, 2007), market selection and industry dynamics in general can benefit from a viewpoint that integrates innovation and multiple, interconnected markets and sectors. In the same way, the study of the pervasiveness of GPT clusters and the effects of technological multipliers could offer useful insights to studies dealing with firms heterogeneity, turbulence, and (decreasing) market dynamism (Decker et al., 2014). In fact, the ultimate determinants of market dynamics may lay in generalized transformations that originate beyond the boundaries of the industries under consideration.

Once GPTs are conceived as dynamic processes, room opens–up for policy discussion. The role of policy intervention in this 'networked' setting cannot be confined to the prescriptions suggested by GPT–based growth models, namely to shorten the 'time to sow' in the equilibrium, GPT–driven, business cycle by influencing the allocation of aggregate resources to innovative activities. Instead, policy–making becomes relevant to identify, and also create, potential GPT clusters. The literature on Smart Specialization Foray (2014), for example, adopts the concept of GPT to suggest that policy makers should be 'promoting GPT networks' by connecting macro–technological change with firm–level learning and discovery processes that have to exploit the prevalent GPT if they want to be successful. In general, this is nothing but a field of application for Industrial Policy. In fact, to understand the dynamic externalities and the technological complementarities induced by a technological multiplier effect is a priority for both industrial and regional policy. The outcome of a GPT–informed policy making is to intervene not just on the rate of innovative activities but on their direction as well, easing a 'division of innovative labor' capable of exploiting the opportunities and the limits of GPT clusters to rewire the network of industrial linkages.

This Chapter has shown that, despite non–negligible conceptual flaws, the GPT theory is endowed with conceptual tools that can be usefully employed to increase our understanding of micro–to–macro phenomena involving technological innovation and industrial linkages. Wright already pointed that out, when he noted that

> (...) the importance of many of the great innovations of the past century (...) was woefully underestimated even by the inventors, because they could not foresee the extent of future improvements in the technology, because the scope for application depended on the unforeseen development of complementary technologies elsewhere in the economy, and because future uses emerged as parts of a complex interdependent system that no one could have predicted in advance. (Wright, 1997, pp. 1561–1562)

The uncertainties related to GPTs establishment make GPTs complex phenomena. This is why to design a fully–fledged theory of GPTs is still an open task. The nature of GPTs and technological multipliers is transformational and enabling, and therefore abstract in nature and empirically elusive. As the notion of 'invention of a method of inventing', suggested by Griliches (1957) and Darby and Zucker (2005) to be at the core of the modern and present–day science–based industrialization, the feature of generality of technologies may not appear straightforward, but it is one of the fundamental ingredients of the continuous change of our economy.

Chapter 4

Competition for the (Downstream) Market: Modeling Acquired Purposes

4.1 Introduction

The pervasiveness (or generality of purpose) of technologies is a feature that economic theory usually disregards or assumes *a priori*. In this paper we posit that the process through which a technology gains pervasiveness matters: The evolution of a technology can result in a broad diffusion or in a failure to spread. The main question to be answered is: How are purposes 'acquired'? Purposes are meant in this paper in the sense of 'applications', or uses for a given technology that can serve as a component, or input, to other technologies or economic activities. Relatedly, we define purpose acquisition process the dynamics leading a technology developed to deploy specific functions or to solve specific problems to identify further purposes and uses than the ones the technology was originally planned or designed for. We focus on a particular setting in which the protagonists are General Purpose Technologies (hereinafter GPTs), upstream technologies (input) characterized by a spectrum of application ranging beyond a single industry or sector and by the capacity to induce economy–wide transformational effects (Bresnahan and Trajtenberg, 1995; Bresnahan, 2010; Lipsey et al., 2005). The relation between GPTs and their applications is a peculiar case of linked markets, where an upstream industry serves multiple downstream industries.

The study of the process of purposes acquisition is relevant because it captures the multilevel nature of the determinants shaping technological trajectories (Dosi, 1982). A contemporary example useful to make clear the issue at stake is that related to the energy–storage and battery sector. As Crabtree recalls,

> In 1991, the year that the lithium–ion battery was commercially released, no one foresaw the disruption that it would cause in personal electronics. After initially being used in portable music players and camcorders, lithium–ion batteries later found their way into, and spurred the development of, laptops, tablets and mobile phones — technologies that have permanently changed how much of society works. Yet there is an even bigger revolution on the horizon. In the same way that telephones had a rotary dial for most of their existence, the electricity grid and cars have mostly existed in a single, unchanged format. But as we move beyond lithium–ion technology, a new generation of cheaper and more powerful batteries will completely rejig the power grid and usher in an age of electrically powered transportation. (Crabtree, 2015)

Taking stock from this quotation means to recognize that i) input technologies are usually introduced for specific purposes and gain pervasiveness later on and ii) the pervasiveness of an upstream incumbent input can be challenged by entrant technologies that try to increase their downstream market share of applications. This Chapter takes these facts as the point of departure to develop a general approach to describe the process of purposes acquisition.

We propose a model of technological competition in a setting featuring vertically–linked markets. A set of downstream industries can adopt one of the possible alternative upstream input technologies that struggle for pervasiveness. The competition among those technologies can result either in the establishment of a new pervasive GPT or in the persistence of the existing GPT as the dominant one. To understand this dynamics, we extend the Schumpeterian concept of 'competition for the market' to the case of vertically related industries, introducing a 'competition for the downstream market'. As the competition for the downstream market unfolds, the process of acquisition of purposes might take place if the new upstream technology prevails on the established one.

We borrow a simple analytical framework used in the literature on international trade to model acquired purposes and to offer a description of how, in a setting featuring linked markets and upstream technological competition, a newly introduced specific purpose technology can become pervasive and, hence, general purpose. The factors affecting the 'specialization' of the downstream industries in one of the alternative upstream technologies are identified and discussed.

The paper proceeds as follows: Section 4.2 defines the building blocks used to intersect theories of linked markets, GPTs and technology evolution. Section 4.3 set up a simple Ricardian model in the spirit of Dornbusch et al. (1977) and Cantner and Hanusch (1993), and outlines some static and dynamic analysis. Section 4.4 concludes discussing the results and suggesting directions for further research.

4.2 Building Blocks: Connectivity and General Purpose Technologies

Given that it deals with linked markets, we consider the study of the process of purposes acquisition part of a more general investigation into the nature of economic connectivity. Indeed, economic connectivity is at the analytical forefront again. Input–output theorists and development scholars have always been interested in the inner structure of connections and bottlenecks (Hirschman, 1958) shaping economies, in order to fine–tune public intervention and to identify the best routes for industrialization processes to escape a handful of 'traps'; on the contrary, standard economic modeling mostly focused its attention either on aggregate dynamics or on industry level structural features.

The analysis of the linkages between industries is recently experiencing a silent resurgence. We outline three main reasons for that, not mutually exclusive: i) New Growth Theory and Schumpeterian Growth Theory did not provide enough explanatory power to explain complex market dynamics, thus inducing scholars to investigate beyond the surface of aggregation and to frame macroeconomic issues (especially fluctuations) as phenomena emerging from localized and micro–level shocks (Acemoglu et al., 2012); ii) network models developed in the context of complexity sciences made their way into economic theorizing, revamping the input–output view of economic activities as a fruitful way to understand and represent production relations, industrial transformations (Carvalho and Voigtländer, 2014; Contreras and Fagiolo, 2014; McNerney et al., 2013), specialization and international trade (Hausmann and Hidalgo, 2011) and the dispersion of manufacturing in global value chains (Timmer et al., 2014); iii) the economic crisis and a timely rediscovery of the role of the public sector in the economy boosted a novel discussion on the aims and tools of industrial policy (Cimoli et al., 2009; Hausmann and Rodrik, 2006; Mazzucato, 2013; Stiglitz et al., 2013) and on the intertwined channels transmitting policy impulses to firms and markets. The idea that ties matter in influencing economic behaviors is certainly not new in innovation economics: The literature on open innovation, collective invention, R&D collaborations and patent networks (Cantner and Graf, 2006) is well developed. Also, the very idea at the basis of the Pavitt taxonomy (Pavitt, 1984) is to highlight industries' external sources of technical change — hence the role played by the connectivity with suppliers, an exercise further developed by a rich literature on rent and knowledge spillovers (Verspagen and De Loo, 1999) and technology flows analysis (Scherer, 1982).

The diffusion of a more network–inspired theorizing due to reasons described above allowed for an increased use of concepts that were confined until recently in niches of the economic discipline as evolutionary, innovation and development economics. Concepts such as multiple equilibria (Hoff, 2000; Stiglitz, 1987; Stiglitz and Greenwald, 2014), learning, ergodic and out–of–equilibrium processes (Arthur, 2013), positive feedbacks, linkages (Hirschman, 1958), all blossom again in the economic literature. These building blocks are helpful to reformulate economic stylized facts as dependent on linked payoffs. More specifically, stating that economic outcomes depend on connectivity — that is on the strength and distribution of linkages between the units of analysis — has consequences for the study of Industrial Dynamics, especially for what concerns some unresolved puzzles. For example, the known technological and economic drivers of market selection (Cantner et al., 2012), market turbulence (Cantner and Krüger, 2004) and industry life cycles (Klepper and Graddy, 1990; Klepper, 1996) may be just a part of a larger story. Connectivity may affect the speed of selection and survival probabilities, the rate and pace of technological change, the duration of the phases of the life cycle. External effects originating in linked markets may play a much broader role in innovation and economic activities than it is usually accounted for. This paper deals with connectivity by studying how the technological specialization of downstream industries (their 'upgrading', in the language of development economics) and the pervasiveness of upstream technologies (input) are related.

The more stylized case of connectivity one can study is that of an upstream–downstream relation between a single supplier and a single customer industry. The literature focuses mainly on incentives and constraints for vertical integration (transaction cost economics being prominent in such type of analysis; see also Arrow (1975) and Bresnahan and Levin (2012)) and on the effects of different market structures on the performance of vertically related markets, for example in the case of double marginalization (Spengler, 1950; Bresnahan and Reiss, 1985). What is interesting is also the endogenous determination of payoffs, when decisions on one side of the relation affect the returns of some activities (for example, innovative activities) on the other side, and vice versa. This is the case, for example, of two–sided markets and platforms (standards) formation (Rysman, 2009; Weyl, 2010) driven by network effects and of organizational ecologies' densities interdependencies (De Figueiredo and Silverman, 2012).

The focus of this paper is a very specific case of connectivity structure, that stands in–between a singular upstream–downstream connection and a complex network structure with multiple upstream–downstream ties. We consider a production structure featuring vertical (that is, hierarchical) relations between one upstream technology and a set of downstream applications and analyze the effects of the introduction of incoming upstream technologies. This structure is similar to what Carvalho (2014) calls a *star economy*, with the difference that here the upstream vertex features several technologies competing for prevalence in use in the downstream industries. A star economy–like structure is the most straightforward representation of the linkages between a GPT (at the center) and its downstream applications (in the surrounding periphery). On this rather general basis, GPT theory has been developed in several economic fields, such as industrial organization (Bresnahan and Trajtenberg, 1995), new growth theory (Helpman, 1998), and evolutionary economics (Carlaw and Lipsey, 2011).

However, the 'generality' of the phenomenon it describes has not yet been exploited to sketch a fully–fledged theory of economic connectivity and linked payoffs in the context of vertically related industries. We fill this gap by extending GPT setting to the case in which the incoming technology striving for pervasiveness is not yet a GPT. When the establishment of a GPT is not assumed a priori, the resulting prevailing and pervasive upstream technology has to emerge from the competition between upstream technologies for the downstream industries. The reason to look at GPTs from this perspective lies in the definitional underpinnings of the very GPT concept (Field, 2008), which 'has come under growing attack' (Ristuccia and Solomou, 2014) recently. To the authors' knowledge, only the paper by Thoma (2009) takes the same viewpoint as the one suggested in the Chapter. The paper studies how potential GPTs 'strive for a large market'. Thoma's analysis focuses on a specific case (Echelon's *LonWorks* control technology) and highlights the different strategies experimented by the company Echelon to foster a pervasive use of its product. These strategies were ranging from value chain integration and collaborations to open sourcing of the product software in order to create a community of loyal users. Eventually, it has been the role played by a big public demander to create the conditions for an increasing pervasive use of the technology. This goes in line with the result of classic GPT models, according to which public procurement can lead the GPT diffusion to higher equilibria. Our contribution goes in the same direction and provides a general framework, rather than a case study, to understand how incoming candidate GPTs succeed or fail while striving for a large market.

In existing GPT models vertical connectivity is key for economic performances and most importantly for innovation performances, given the existence of the so–called 'dual inducement' of innovational complementarities between the single upstream generic technology and downstream applications. The problem in that context is to determine and solve the coordination issue arising between downstream applications and a pre–determined upstream technology. Market outcomes can be lower than socially desirable, however, there, coordination is about the intensity, rather than the direction of innovative activities. In our paper, also the direction matters, in the sense that the incoming upstream technology is not aware of its potential GPT 'status'; it learns it through its (successful or not) dynamics toward prevalence, persistence, and pervasiveness (see Chapter 2). User industries can choose the upstream technology to which to be tied; the outcome in terms of which upstream technology prevails decides the direction innovation activities.

Modeling a star economy in the making is closely connected with three strands of literature: First, there are similarities with models dealing with infant industries and early stages of industrialization (Hausmann and Rodrik, 2003; Hoff, 1997). In fact, one may think of the process leading to the establishment of a GPT as a case of 'infant technology' development. Second, modeling the problem of 'acquired purposes' closely resembles the phenomena on which studies on competing technologies (Arthur, 1989) focus on, namely dynamic increasing returns to adoption. Third, modeling the switch between upstream technologies by downstream industries can be framed as a standard topic in industrial dynamics, that of entry/exit patterns. In this case those entering are not firms; it is an entire application industry that, by adopting one of the upstream competing technologies, enters in one of the potential GPT sectors.

Our model builds upon the classic (Bresnahan and Trajtenberg, 1995, hereinafter BT) model.[1] There, the authors explore the simple 'star economy'

[1] In what follows we refer to the journal version of the study, dated 1995. In case the contents of interest are available only in the extended working paper version we refer to

case, the one featuring a vertical relationship between industries. The basic structure of the model is a 'hierarchical pattern' of technological interdependence between one GPT industry and many downstream application industries/sectors (hereinafter AS). BT define an AS an industry/sector 'that (i) is an actual or potential user of the GPT as an input; (ii) can earn positive returns by engaging in R&D of its own; and (iii) the rents it earns increase monotonically with the "quality" of the GPT' (Bresnahan and Trajtenberg, 1992, p. 11).

In short, the BT model features a coordination game in innovative activities with one–to–many upstream–downstream linked payoffs. These generate on the one hand a potential positive feedback process in innovation (a so–called dual inducement mechanism) and, on the other hand, suboptimal equilibria due to a vertical and a horizontal externality. The vertical externality emerges from the linked payoffs between GPT and AS — it is a bilateral moral hazard problem; the horizontal externality results from the linked payoffs between the many ASs given their indirect connection through the GPT. The main variables affecting the two types of sectors' optimal decision making with regards to innovative activities (the objective functions to be maximized being the expected gross returns on innovative activities for the AS and the expected profits for the GPT) are z (a scalar for the GPT technical 'quality'), w (the price of the GPT input) and c (the constant marginal cost of production of the GPT–embodying commodity for the GPT sector). This set of variables proxy both economic and technological explanations affecting the GPT–AS coordination game.

In BT, there is no alternative to an already established GPT. The possibility that a pseudo–diffusion (GPT adoption by the ASs) process takes place within this game is captured by assuming an invariant ranking of ASs with respect to $V(w, z)$ (the ASs' value function of innovation gross rents) and letting z and w to vary in order to determine the unique 'marginal' or threshold AS that finds profitable to adopt the GPT (Bresnahan and Trajtenberg, 1992). Formally, 'for $n(w, z)$ indicating the largest number of AS that finds profitable to use the GPT as input given w and z, then $n_w(w, z) < 0$, $n_z(w, z) > 0$' (the subscript indicating the partial derivative of

the source dated 1992.

n with respect to w and z), meaning that, 'the set of using sectors expands as the quality of the GPT improves and its price goes down' (Bresnahan and Trajtenberg, 1992, p. 13). The adoption process captured by the changes in $n(w, z)$ is already a broad proxy for a dynamics of purposes acquisition, if one assumes that ASs are heterogeneous and that therefore an increase in the number of downstream adopters widens the set of functions and uses the GPT provides. This is correct, however only because it is *given* in the model the presence of a single already established GPT. The change in the number of AS adopting an upstream input does not depend on the upstream competition among alternative technologies struggling for success and pervasiveness. We extend this process having in mind the general case with several potential GPTs j and with $n_j(w_1, w_2, \ldots, w_j, z_1, z_2, \ldots, z_j)$, that is the number of ASs 'choosing' a potential GPT j is function of the quality and the cost of all the relevant alternatives.

Besides the rationales derived from the relevance of studies on economic connectivity and from the received IO–based GPT theory, the Chapter main question is also justified by a further theoretical argument that has to do with the representation of the process of technological takeover. This process is usually related to the phenomenon of 'disruption'.[2] Adner and Zemsky (2005) offer a formal discussion of the conditions for technological disruption to occur. The authors explore the economic conditions and the timing under which a novel technology either invades a mainstream market or remains confined in a niche, for the case featuring two competing technologies and heterogeneously distributed firms' willingness to pay. Even if the argument there is not made explicit, the model can be framed as one of firms' technological specialization in upstream competing technologies and goes in the same direction taken by this paper — to show that multiple equilibria are possible outcomes in a vertically related market with linked payoffs and more than one potential GPT available. Adner and Levinthal (2002) bring the analysis of purposes acquisition on the terrain of evolutionary theory by comparing the pervasiveness in the making of a technology with the phenomenon

[2] Despite the similarity of the concepts of generic technological change and disruption, the two have only a partial overlap. The progressive establishment of a GPT may or may not produce disruption. Its establishment as an emerging pervasive input can be characterized by re–domaining (Arthur, 2009) of existing activities around new physical principles and by the generation of complementarities, rather than substitution.

of speciation. Speciation in the economy is *the application of existing technologies to a new domain of application* (Adner and Levinthal, 2002, p. 51), just as a candidate GPT gains shares in the downstream application domain. A close — though distinct — similitude is that with the concept of exaptation (Andriani and Cohen, 2013; Dew et al., 2004). Exaptation occurs *when traits get co–opted for use in unintended ways* (Andriani and Cohen, 2013). Speciation and exaptation processes are conceptually proximate with what is labeled technological upgrading in Development economics, re–domaining in Complexity economics (Arthur, 2009) and technological convergence in the Economics of technical change (Rosenberg, 1963). In a broad sense, the core idea is that in the struggle for pervasiveness, the more downstream applications switch to use one of the upstream inputs so that it starts to be used in new domains, the more the economy experiences a technological structural change.[3]

In sum, we can highlight the following theoretical building blocks that will be used in the remainder of the analysis: i) technology adoption and technological competition depend both on economic and non–economic (in this case, technological) determinants, that can be considered independently from each other; ii) the adoption/diffusion of an incoming upstream technology is function of the change in the economic and technological determinants across all the relevant alternatives; iii) an incoming upstream technology striving for pervasiveness can encounter resistance from the established GPT; iv) purposes are acquired in an evolutionary manner, either co–opting functions for use in unintended ways or applying existing functions to new domains. In what follows the building blocks discussed above are used to set up a toy model that represents how an upstream potential GPT can succeed or fail to acquire purposes.

[3] With technological structural change we mean here a transformation of the technological base of industries rather than — as usually meant for structural change — a shift in employment allocation through macro–sectors.

4.3 A Ricardian Model of Technological Specialization

We propose a simple model that represents the dynamics of purposes acquisition when more than one upstream technology is available in the market. The outcome of this competition for the downstream market may vary according to the state and change of the economic and technological variables at work. We distinguish three broad outcomes of the model: i) in the competition between an established and a new upstream technology, the new upstream technology gains pervasiveness in the market and in the limit takes over and 'serves' the whole downstream economy; ii) in the competition between an established and a new upstream technology, the established upstream technology maintains its pervasiveness in the economy and a novel one occupies only a niche (it is adopted by none or a limited amount of downstream sectors); iii) in the competition between an established, a new and a third, newer, upstream technology, the third, newer upstream technology displaces the new one, making the former a sort of 'failed GPT'.

The model is a simplified version of the Dornbusch et al. (1977) assignment model of international specialization in line with Cantner and Hanusch (1993), Acemoglu and Autor (2011); Cimoli (1988); Dosi and Soete (1983) and, more recently, Costinot (2009) and Costinot and Vogel (2015).[4] In our version the matching occurs between upstream technologies (industries) and downstream industries, rather than countries and products as in Cantner and Hanusch (1993) and skills/labor and tasks as in Acemoglu and Autor (2011). The units of analysis of the model are generic individual industries; firms' behavior is not explicitly taken into account. We assume homogeneity between firms and heterogeneity between industries; while barely realistic (stylized facts regarding the persistent 'fractal' nature of economic characteristics the more disaggregation is deepened are well–known, see Dosi and Nelson (2010)) the introduction of firms heterogeneity would only magnify a phenomenon already emerging under more simplifying restrictions. For the sake of generality, hereinafter instead of the term 'downstream industries' we use the term 'downstream applications', in order to take into account a

[4]The model itself can be conceived as a case of exaptation, given that a framework developed for a specific purpose is imported into another field of economic theorizing.

more disaggregated and richer set of economic activities.

The next sub–section describes the case featuring two–upstream industries — one established and a new upstream technology. Later on, we extend the analysis to a three–upstream industries scenario.

4.3.1 The Case of Two Competing Upstream Industries

We assume that each upstream industry produces a single technology.[5] The upstream technology is in turn used as a single component in downstream applications. The structure is that of a value chain with two layers: that of the suppliers (upstream) and that of the user (downstream) industries. Upstream industries are labeled with the index E (for the established technology) and N (for the new technology). Technology N is a potential 'entrant' in the upstream market; furthermore, it is reasonable to assume that N is associated with a limited set of specific downstream industries initiated thanks to the very discovery or invention of N. Given that downstream applications' production technologies depend only on the upstream product, they can be characterized by their valuation of the specific upstream technologies and ordered in a continuous and closed interval $[0; I_n]$, where I indicates a generic downstream application and n is an ordered index.

In Cantner and Hanusch (1993) goods are characterized by a labor requirement (the inverse of labor productivity) needed to produce them, with a decrease in labor requirement capturing an increase in production efficiency. In our model we look at industries or downstream applications (instead of goods) and we assume that — due to strong complementarities — the upstream components quantity requirement is constant (and normalize it to one unit) and what changes are just the benefit of using one or the other upstream technology, that in BT are captured by the 'quality' of the GPT. The ranking over the continuum of downstream applications, which is assumed to be invariant over time, distributes the downstream application according to the *relative* benefit of using the new upstream technology. Relative benefit measures the advantage or the disadvantage for a downstream

[5] By doing so the use of the terms upstream industry and upstream technology in the paper is indifferent.

application to 'attach' to the new upstream industry compared with the choice of staying with the established one. This is a measure that proxies in a scalar a number of innovation determinants that are well known in the literature, such as technological intensity or performance gap (Cantner and Hanusch, 1993, p. 220), technological opportunities (Klevorick et al., 1995), price/performance sensitivity (Almudi et al., 2013; Dosi and Nelson, 2010; Pavitt, 1984) or relative willingness to pay for the upstream technologies. In turn, all these concepts are potential proxies for the easiness of technology switch from an established to a new upstream technology, and capture the core of the technological side of our model.

In order to keep a degree of consistency with the previous literature, the model uses the same set of explanatory variables and a similar notation to that outlined in the building block Section. The measures of benefit outlined above can be interpreted as functions of the perceived *usefulness* of (one of) the (potential) GPTs. We call $z_j(I)$ such application–dependent usefulness, where $j = \{E, N\}$, E is the established and N the novel upstream technology and z varies in I. The specific feature of our model is that we are discussing *relative* rather than *absolute* usefulness — that is a measure for 'comparative advantage' of technology N with respect to technology E. Therefore, our variable of interest is $\zeta(I) = \frac{z_N(I)}{z_E(I)}$, the relative technological usefulness (attractiveness) of upstream technologies. It is important to highlight here that while in Bresnahan and Trajtenberg (1995) model z is a single scaler value (the GPT 'quality') known to all the AS, in our case z is a downstream application's valuation of the upstream technology quality. The model is deterministic, that is we do not interpret z as an 'expected' usefulness but as a source of heterogeneity between applications. In this way, heterogeneity is introduced in the model via a continuous distribution of downstream propensities to choose the performance of N relatively to E and the model can be considered belonging to the class of *probit or threshold models of diffusion* (Geroski, 2000).

Given that it is defined over the interval of downstream applications, $\zeta(I)$ is a function — the relative (upstream) technology usefulness (performance) curve. Following Cantner and Hanusch (1993) we make the following assumptions on the shape of $\zeta(I)$: i) it is continuous and differentiable in

$[0; I_n]$; ii) it is monotonically increasing in I due to the downstream applications' ordering, with $\zeta' > 0$; iii) it is reversible ($\zeta^{-1}(I)$ does exist). In short, $\zeta(I)$ represents the comparative increasing rewards obtained from purchasing the new upstream component rather than using the established one. At this point, it has to be added that downstream sector size does not play a role in the model; each downstream application, defined over an infinite continuum, has an infinitesimal size with respect to the whole economy. Theoretically speaking, sub–intervals of technologically proximate (in the comparative advantage space) applications can be identified and aggregated in order to model different industries sizes and to provide a more realistic representation of the unequal weight of downstream economic sectors in the economy. Such a refinement is left aside in this version of the model, even if downstream sector size may play a role when mutual feedbacks and linked payoffs are explicitly formalized and taken into account.

In order to have an upstream–downstream markets matching, the technological dimension has to be confronted with an economic dimension of the relation. More precisely, the technology relative usefulness (performance) curve has to be coupled with a relative cost curve. In Dornbusch et al. (1977) and in Cantner and Hanusch (1993) the corresponding curve is a demand curve that integrates consumption shares over the continuum of goods given the Cobb–Douglas preferences of consumers. Here we simplify the object of analysis by displaying only the relative cost for downstream sectors to acquire upstream technologies. If each downstream application purchases a constant amount of upstream component (we assumed only one unit), then no demand curve exists to determine the pricing of the potential GPTs. What matters is the relation between the two costs. Again consistently with Bresnahan and Trajtenberg (1995) we define $w_j(I)$ as the cost of the upstream technology, where $j = \{E, N\}$, E is the established and N the novel upstream technology. We do not deal with price–cost margins (profits) in the upstream market, because the change in the downstream shares using one or the other upstream technology is completely driven by downstream applications' adoption decisions.[6] The ratio $\omega(I) = \frac{w_N(I)}{w_E(I)}$ represents the relative cost (downstream expenditure) curve. Regarding the shape of

[6] However, price–cost margins may be quite relevant in affecting the magnitude of vertical externalities (Bresnahan and Trajtenberg, 1995).

$\omega(I)$ the assumptions we made on $\zeta(I)$ on continuity and differentiability hold. Concerning the slope of $\omega(I)$, we can imagine three possibilities: i) *ceteris paribus* the downstream applications' ranking, the novel upstream technology will be relatively more (less) costly for downstream applications with a comparative disadvantage (advantage) in switching: $\omega(I)$ is monotonically decreasing in I; ii) $\omega(I)$ is constant over the whole distribution of downstream application because either $w_N(I)$ and $w_E(I)$ are constant for all I or are monotonically decreasing at the same rate over I; iii) $\omega(I)$ is non–monotone. Formulation i) and ii) are more straightforward for comparative statics purposes, while iii) may produce multiple equilibria. In the remainder of this Section, we assume that cases i) or ii) apply.[7]

In general, the model determines an industry I_e that separates the market between applications using upstream technology E and applications using upstream technology N. To determine I_e, over the interval $[0; I_n]$ we can set into relation the relative usefulness and the relative cost of the upstream technologies for each downstream application I

$$\frac{z_N(I)}{z_E(I)} \lesseqgtr \frac{w_N(I)}{w_E(I)} \rightarrow \frac{z_E(I)}{w_E(I)} \lesseqgtr \frac{z_N(I)}{w_N(I)}$$

which transforms in a usefulness/cost ratio $\frac{z_j(I)}{z_j(I)}$. By the properties of the ζ– and the ω–functions there is a downstream application I_e for which the following holds:

$$\frac{z_N(I)}{z_E(I)} = \frac{w_N(I)}{w_E(I)} \rightarrow \frac{z_E(I)}{w_E(I)} = \frac{z_N(I)}{w_N(I)}$$

A downstream application adopts N if $\frac{z_E(I)}{w_E(I)} < \frac{z_N(I)}{w_N(I)}$. In I_e the equality sign holds and the model yields the unique threshold or borderline downstream application that is indifferent in the choice of upstream technology. In addition to the identification I_e the model simultaneously provides the size of intervals $]0, I_e]$ and $]I_e, I_n]$, which are the shares of the downstream

[7] One may discuss if to identify a single 'net benefit' curve by defining a function $\nu(I) = \zeta(I) - \omega(I)$ could be an equivalent modeling strategy. We prefer to distinguish the two functions to highlight the role played by both technological and economic determinants.

market specialized either in E or N. A measure or a metric can be derived for the length of the $]0, I_e]$ and $]I_e, I_n]$ intervals, and used to assess the pervasiveness and thus the 'GPT nature' of the upstream technologies and to track the dynamics of the purposes acquisition process.

The endogeneity of $\zeta(I)$ and $\omega(I)$ curves' determination is purposefully avoided in the model, in order to distinguish the effect of purely technological and pure economic determinants of the downstream specialization towards one or the other upstream industry. The feedback effects both on the demand and supply side can be already detected by fractioning the dynamic adjustment process of specialization in one or the other upstream technology in a sequence of 'screenshots'. In line with Gans (2011), static analysis can already be a sufficient proxy for dynamics considerations in some cases. For example, the presence of dual inducements — downstream adoption improves the quality of the upstream and vice versa — can be modeled as shifts towards the left of the $\zeta(I)$ curve, while the presence of learning effects (Arrow, 1962; Thompson, 2010), meaning that the gains in efficiency of one technology production (in general or respect to the competing alternative) are captured by a movement on the left of the $\omega(I)$ curve (with $w_N(I)$ decreasing faster than $w_E(I)$). The presence of dual inducements or faster learning effects in the established technology may also give rise to non–linearities (and therefore potentially to multiple equilibria) in the both demand and supply relative curves, a possibility here ruled out by our assumption on the shape of $\zeta(I)$ and $\omega(I)$.

A graphical representation of the outcomes of the model is provided in Figures 4.1 and 4.2. The two different cases provided are discussed next.

4.3.2 Discussion on the Two–upstream Technologies Case

As anticipated at the beginning of the paragraph, two are the main outcomes of the two–upstream technologies case. We can label them as the *competition (and potential takeover)* case and the *niche case*. They respectively mirror the 'Ricardo case' and the 'innovation case' in Cantner and Hanusch (1993). In the competition case (see Figure 4.1), the intersection of $\zeta(I)$

and $\omega(I)$ determines the downstream economy's specialization, which at the very beginning may feature the established upstream technology to maintain its 'control' over a wide share of downstream applications. Varying the comparative (relative) advantages in upstream usefulness and cost, the new upstream industry starts to acquire purposes (that is, the borderline downstream industry moves to the left), leading in the limit to a full takeover. In this sub–case, the new upstream technology may well be labeled as a GPT, but only after a process that put it in the position to serve the largest share of the downstream market. The new upstream technology enters the market as a specific purpose technology, gains pervasiveness and acquires purposes until it dominates the downstream market and becomes a GPT.

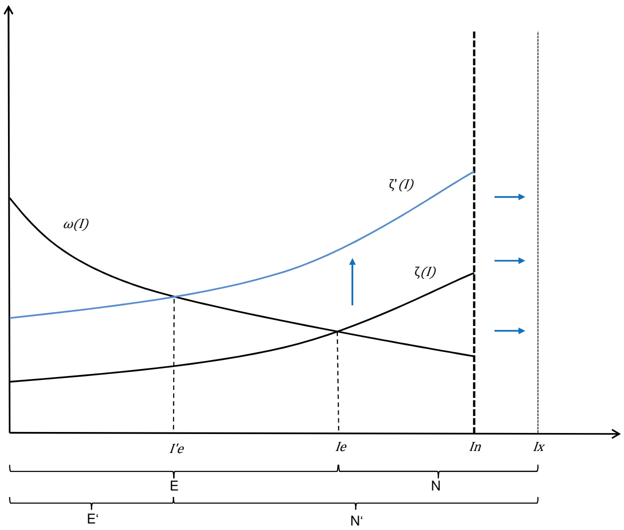

Figure 4.1: Competition case

Note: the shift in the $\zeta(I)$ curve indicates an increase in comparative advantage for the new upstream technology. Shares E, E', N and N' indicate the result of the competition for the downstream market, respectively for technology E and N before and after the change in relative usefulness. The rightmost interval $[I_n, I_x]$ indicates the set of novel downstream industries that come together with the new upstream technology — there the $\zeta(I)$ curve is not defined.

In the second scenario (see Figure 4.2), that we label niche case, $\zeta(I)$ and $\omega(I)$ do not intersect, so that despite the increasing attractiveness and comparative advantage of the new upstream along the distribution of downstream applications the technological argument does not compensate for the economic one, with $\omega(I)$ lying completely above $\zeta(I)$, so that $I_e = I_n$. In this case a novel upstream technology and potential candidate to become a pervasive GPT fails to emerge as such (van Zon et al., 2003) and remains a niche component used by a very limited set of applications, at the limit only those new downstream applications emerged due to the introduction of the new upstream technology in the economy. A niche case can always turn into a competition/takeover case, when a shift to the left of $\zeta(I)$ or a shift to the left of $\omega(I)$ re–establishes an intersection between the two curves and sets $I_e < I_n$, meaning that the borderline downstream application is an internal point of the interval.

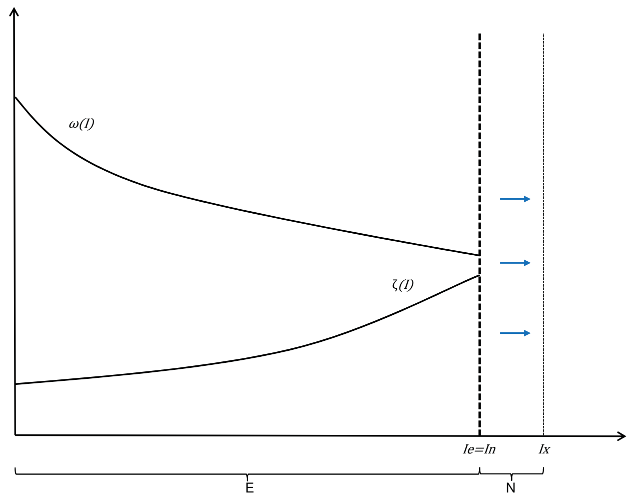

Figure 4.2: Niche case

Note: the relative usefulness of the new upstream technology does not compensate for the relative cost along all the downstream continuum of industries. Only the novel downstream industries that emerge together with technology N adopt it. N never succeeds in acquiring purposes.

The model can also account for the consequences generated by the emergence of new downstream applications (for example novel downstream products and infant economic activities) that, as mentioned earlier, may follow the introduction of N.[8] This is formalized by extending on the right side the

[8]The appearance of new downstream sectors can be also understood in the terms of Bresnahan and Yin (2010), as the emergence of latent sectors whose demand was beforehand unserved under the dominance of the established upstream technology.

interval $[0; I_e; I_n]$ to $[0; I_e; I_n; I_x]$. Here $[0; I_e[$ indicates the interval of applications attached to the established upstream technology and $]I_e; I_n; I_x]$ indicates the extended interval. This includes the existing applications adopting the upstream technology N, from the borderline I_e to I_n and those just entered in the market, labeled with x and identified in the additional interval $]I_n; I_x]$. In the niche case I_e and I_n will coincide. We assume that newborn downstream applications can produce for the final market only if connected to the new upstream technology, meaning that they do not evaluate comparative advantage (formally, they have an infinitely high comparative advantage in $\zeta(I)$ and an infinitely low $\omega(I)$). New downstream applications add in an ordered succession to the ranked distribution of the downstream market. The presence of newborn downstream applications provides upstream technology N with a 'buffer' stock of users. In a dynamic setting featuring positive feedbacks from the number of adopters to the increasing comparative advantage in adoption (meaning that $\dot{z}_j$ and/or $\dot{w}_j$ are function of the sizes of the applications intervals served), such a stock may trigger a purposes acquisition dynamics leading N to become a GPT. In this sense, the new upstream technology enters the upstream market as a specific purpose technology and its applications are only those downstream links existing at its 'birth'. If the user base in these downstream industries is large enough, the relative usefulness of N is affected positively, leading to an upward shift of the $\zeta(I)$ curve or to a downward shift of $\omega(I)$, depending on how network effects are modeled. This, ceteris paribus, increases the size of the downstream interval served by N; in practical terms this means that N diffuses through the heterogeneous downstream industries, increasing its applicability and, therefore, acquiring purposes.

4.3.3 Three Competing Upstream Industries

The static model outlined above can be extended to the case of three (or more) upstream technology. Following Acemoglu and Autor (2011), we introduce in the set of upstream technologies a newer one, labeled M. Given that downstream applications already face the decision to stay or switch between E and N depending on the value and shape taken by the relative usefulness and relative cost curves, to find the new upstream–downstream market matching with three upstream alternatives it is sufficient to derive two new curves, describing the comparative performance and cost between upstream technologies N and M. Assuming that the ranking of downstream applications remains unchanged, we rename $\zeta(I)$ and $\omega(I)$ as $\zeta_{EN}(I)$ and $\omega_{EN}(I)$ and introduce $\zeta_{NM}(I)$ and $\omega_{NM}(I)$ as the two new comparative relations. The same assumptions on continuity, monotonicity and reversibility hold. Figure 4.3 presents the scenario just discussed.

Shifts of in $\zeta_{EN}(I)$, $\omega_{EN}(I)$, $\zeta_{NM}(I)$, and $\omega_{NM}(I)$ may lead to a broader set of technological specializations in the economy. Once again, the established upstream technology may maintain its prevalent role in the economy, the new upstream may take over downstream market shares becoming prevalent (that is, acquiring the status of GPT) or the newer upstream may substitute for the new one, making the latter a failed potential GPT and the former a pervasive technology. Finally, the downstream market may well be split among the three competing upstream, avoiding the tendency for any GPT to appear. The three upstream technologies case can be further extended to a many–to–many relations assignment model, with a continuum of downstream applications matching with a continuum of upstream technologies (see Costinot and Vogel (2015) for such a generalization in the case of Ricardian trade models). However, the three upstream industries case is already general enough to highlight the main result of this paper: the standard GPT model is just a special case of a model of competition for the downstream market by upstream technologies that can display a richer set of outcomes and structural configurations.

In fact, such generalization has the virtue to show how technological competition for the downstream market may be resolved in a broad constellation of outcomes, with only some of them leading to the replacement of a GPT with a new one and to a successful process of purposes acquisition and increase in generality, applicability and pervasiveness for one of the upstream technologies. Furthermore, the three upstream technologies case provides another insight on the process of technological competition in vertically related markets: the higher the number of upstream technologies, the bigger the number of variables affecting the final outcome. Relative usefulness and relative costs can all be subject to change, and, therefore, the determinants

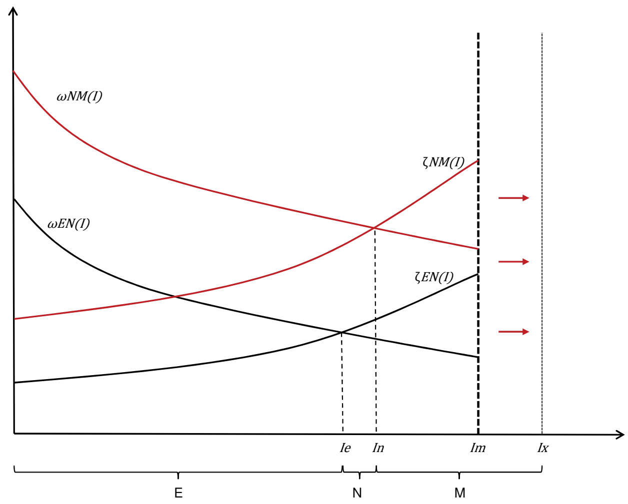

Figure 4.3: Three–upstream technologies case

Note: the arrival of a newer upstream technology M increases the competition for the downstream market based on comparative advantages and costs. In this case, the newer technology 'steals' downstream market shares to N, and the whole market is shared on rather equal basis by the three alternative upstream technologies.

of purpose acquisition may be non–trivial to identify. This, on the other hand, means that also the 'levers' to affect the results of upstream technological competition multiply — opening room for a wide set of possibilities for policy intervention.

4.3.4 Policy Interventions

The static model also allows for basic policy 'experiments'. From Bresnahan and Trajtenberg (1995) we know that, in a GPT framework, policy intervention in the form of well–designed contracts and public procurement is a condition to solve the coordination problem and to select better (higher) equilibria by exploiting the dual inducement mechanism and internalizing the vertical and horizontal externalities. In fact, 'learning is just part of the story: independent scientific advances as well as massive investments in purposive R&D have contributed as much to the staggering pace of technical advance (...)' (Bresnahan and Trajtenberg, 1992, p. 8). Such 'massive investments in purposive R&D', realized either supporting private actors or by directly intervening in the economy can be included in the Ricardian model. Policy interventions affect either the usefulness or the cost of the upstream technologies, and can be therefore by expressed as discrete changes in z's and w's. Accordingly, $\Delta z_j(I)$ and $\Delta w_j(I)$ are the magnitudes of policy interventions, where $j = \{E, N\}$ indicates that policy can affect one, the other, or all the upstream technologies. Policy can intervene either on the economic or technological side, in a well–known policy–mix fashion.

For example, a policy easing the establishment of contacts and linkages among firms belonging to different industries (e.g. a cluster policy or the support to multidisciplinary science parks) affects the usefulness dimensions. Better information on the features of the upstream technologies, resulting from policies designed to favor exploration and experimentation can change the downstream distribution of thresholds for adoption. On the economic side, subsidy and tariff schemes influence the relative cost of the established technology compared to the new one. Interventions of this kind are evident in the case of upstream competition among alternative energy supply technologies, where governments support the entrant upstream technologies — namely renewable technologies — intervening on the relative prices discriminating by the source of energy.

A purposive 'push' in one of the upstream shifts the borderline application (applications, in the three upstream technologies case), helping one or the other upstream component to defend its share of downstream user from the competing technologies or to ease the process of purposes acquisition. In short, public intervention can act on different upstream levers, leading the system to one out of many possible specialization patterns. Public policy can also decide to allocate its efforts to sustain different upstream technologies at the same moment with the objective to explore different trajectories in parallel Cohen and Klepper (1992).

Policy interventions, therefore, affect not just the intensity of innovative activities, but their direction as well. An interesting point to be mentioned in this context is that the possibility of parallel explorations of different trajectories (upstream technologies) allows the economic system as a whole to screen a wider set of states of the world. However, the allocation of resources to alternative and competitive ends reduces the 'demand effect' that has been identified as key to kick–in dual inducement dynamics; this, in turn, raises the chances that a potential GPT gets locked into an inferior equilibrium in terms of performance and size of the user base.

4.3.5 A Simple Dynamic Setting

The static version of the model can already suffice to illustrate the main claim of the paper: when more than one candidate GPT compete as an upstream technology for a downstream market of applications, a potential GPT can either succeed or fail to gain pervasiveness. A GPT is not anymore assumed to exist a priori in the economy — the case is instead that of a specific–purpose upstream technology that acquires purposes and becomes a GPT. A dynamic extension of the model can, however, shed some light on how different outcomes in the competition for the downstream market are obtained, meaning how different equilibria in the structure of specialization of the downstream economy can be reached. Dynamic models of technology competition and diffusion such as the one in Loch and Huberman (1999) describe how adoption of alternatives evolves over time, usually modeling it as function of performance, in turn affected by network effects. The case described in this model is, however, different, since the population of adopters (the downstream applications) is heterogeneous. This means that performance does not depend only on technology characteristics (for example, expected returns or profits) and market characteristics (the magnitude of network externalities) but also on application–specific preferences (thresholds) that are captured by the shape of the $\zeta(I)$ curve.

Let's consider again the two–upstream technologies case. A dynamic version of the model has to determine the law of motion of three variables: $\zeta(I)$, $\omega(I)$ and I_e. Following Cimoli (1988), it is useful to derive first a scalar measure for the responsiveness of the downstream specialization to changes in the fundamental technological and economic conditions. To ease the reading, the functions $\zeta(I)$ and $\omega(I)$ are indicated as ζ and ω. We define

$$\epsilon_{I_e,\omega} = \frac{\partial I_e}{I_e}\frac{\omega}{\partial\omega}$$

as the comparative costs elasticity of the borderline downstream application. $\epsilon_{I_e,\omega}$ indicates, for a given $\zeta(I)$ function, the percentage change in borderline application given a percentage change in the relative cost of the two upstream technologies. As the new upstream technology gets more expensive (cheaper) relatively to the established one, the threshold downstream sector moves rightwards (leftwards) at a higher rate the higher is $\epsilon_{I_e,\omega}$. A similar expression can be derived for the comparative usefulness elasticity of the borderline downstream application, $\epsilon_{I_e,\zeta}$, where

$$\epsilon_{I_e,\zeta} = \frac{\partial I_e}{I_e}\frac{\zeta}{\partial\zeta}$$

indicates the percentage change in the borderline application given a percentage change in the relative usefulness of the new upstream technology with respect to the established one. The higher $\epsilon_{I_e,\zeta}$, the bigger the share of downstream market the new upstream gains (lose) if its quality improves (worsen) relatively to the established one.

The dynamics of I_e can be modeled as follows:

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e(\epsilon_{I_e,\omega}\epsilon_{I_e,\zeta})\left[\dot{\zeta}(I) - \dot{\omega}(I)\right] \tag{4.1}$$

where a dot indicates the rate of change of a variable and t is the time index. The dynamics of the borderline downstream application is function of the current state I_e, of the elasticities and of the net absolute changes of the relative usefulness and cost curves. These can be expressed as

$$\frac{\partial\zeta(I)}{\partial t} \equiv \dot{\zeta}(I) = \hat{z}_N - \hat{z}_E \tag{4.2}$$

$$\frac{\partial\omega(I)}{\partial t} \equiv \dot{\omega}(I) = \hat{w}_N - \hat{w}_E \tag{4.3}$$

where a hat over a variable indicates a growth rate (percentage change). Each comparative curve evolution results from the net change between the numerator and the denominator. Inserting equations 4.2 and 4.3 into 4.1 we have

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e(\epsilon_{I_e,\omega}\epsilon_{I_e,\zeta})\left[(\hat{z}_N - \hat{z}_E) + (\hat{w}_E - \hat{w}_N)\right] \tag{4.4}$$

Functional forms are kept implicit until now. In order to identify an equilibrium I_e, we need to specify them. It is reasonable to assume that either the relative usefulness or the relative cost is affected by network effects (Arthur, 1989; Farrell and Klemperer, 2007), that is, by the number of downstream application attached either to N or E. Another way to measure the network effect is by the size of the intervals $]0, I_e]$ and $]I_e, I_n]$. Setting $I_n = 1$ (meaning that we fit the continuum of downstream applications to the unit support),[9] the number of downstream users of E is I_e, while the number of downstream users of N is $(1 - I_e)$.

On the performance side, introducing network effects equals to say that as the gap in usefulness widens, the more downstream applications switch to use upstream technology N. On the cost side, the network effects play a role on the steepness of learning curves: the more downstream applications switch to N, the faster the new upstream technology can reduce its price. Since the focus of the paper is that to model acquired purposes, we assume for consistency that network effects play a role only on the performance side: as diffusion of the new upstream technology takes place, the relative usefulness perceived increases. This is a proxy for the process of discovery of new purposes that over time makes a specific purpose technology to gain pervasiveness downstream and to become a GPT. Of course, in real–world contexts network effects do play a role on both the technological and the economic side.

As a caveat, it is important to remark here that the network effects as modeled in this Section are not an exact proxy for the dual inducement mechanism that in Bresnahan and Trajtenberg (1995) takes place between

[9] Or $I_x = 1$, in case new downstream industries emerge together with N.

the single GPT existing in the market and its application. In fact, while the dual inducement is limited to incentives to innovative activities, here we take a broader perspective that incorporates technological and economic determinants. Moreover, downstream industries do not optimize over any choice variable, but just react to upstream relative performance and cost. In our model, however, an increase in relative usefulness triggers an increase in downstream adoption, and vice versa. A mutual feedback in similar to the dual inducement mechanism is therefore indirectly captured.

We assume for the moment that upstream technology purchasing costs for E and N are the same for each I (since all downstream applications purchase one unit of upstream component at the same price from the same supplier), so that $w_{j,I} = w_j$ for $j = \{E, N\}$ is constant over the downstream continuum. The dynamics of w_j follows a simplified learning curve over time of the type

$$\dot{w}_j = -\gamma_j w_j \tag{4.5}$$

with $\gamma_j = -\hat{w}_j$ as the (negative) upstream technology constant (and technology specific) percentage rate of cost reduction. As concerns performance, we model improvements in usefulness — and thus acquisition of purposes — as a function of downstream adoption. The process of performance improvement is usually represented as following an S–shaped pattern (Loch and Huberman, 1999); here we opt for a simpler linear version:

$$\dot{z}_N = \theta_N z_N(I)(1 - I_e) \tag{4.6}$$

$$\dot{z}_E = \theta_E z_E(I)(I_e). \tag{4.7}$$

We assume also that the z function takes the shape $z_j(I) = e^{\alpha_j I}$ for $j = \{E, N\}$, to represent the monotonically increasing property of upstream technology usefulness along the downstream continuum. α is a technology specific scaling parameter, while θ captures an exogenous rate of technological improvement that is also dependent on the upstream technology chosen. From this, equations 4.6 and 4.7 become

$$\dot{z}_N = \theta_N e^{\alpha_N I}(1 - I_e) \tag{4.8}$$

$$\dot{z}_E = \theta_E e^{\alpha_E I}(I_e) \tag{4.9}$$

and the respective growth rates

$$\hat{z}_N = \theta_N(1 - I_e) \tag{4.10}$$

$$\hat{z}_E = \theta_E(I_e) \tag{4.11}$$

The percentage change in the usefulness of E and N depends therefore only on the exogenous parameter and — endogenously — on the respective downstream market shares.

Inserting 4.5, 4.10 and 4.11 in 4.4 we obtain

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e(\epsilon_{I_e,\omega}\epsilon_{I_e,\zeta})\left[(\theta_N(1 - I_e) - \theta_E(I_e)) + (\gamma_N - \gamma_E)\right] \tag{4.12}$$

The structural equilibrium is identified when $\dot{I}_e = 0$, where the changes in relative usefulness and relative cost perfectly compensate each other. One trivial equilibrium is obtained in the corner solution in which N fully dominates the market. This occurs, that is when $I_e = 0$. This means that, using the categories introduced in the static setting, only in the niche case,[10] when relative usefulness and cost do not intersect, the new upstream fails to gain pervasiveness and to become a GPT. As soon as N is adopted by a minimum

[10] And only assuming that the interval $]I_n, I_x] = 0$ or that the downstream industries that emerge together with upstream technology N do not generate any network effect.

share of downstream application, the system moves to the stable equilibrium in which $I_e = 0$, as shown in Figure 4.4. For N to fail to gain pervasiveness equation either one or both the elasticity terms are zero (meaning that one or both the curves are rigid), or 4.12 has to show multiple equilibria. However, this is possible only when non–linearity in the shape of the curves is introduced. We do that relaxing the assumption that costs change uniformly along the downstream continuum. One justification for this is related to the possibility for the established upstream technology to 'fight back', meaning to actively respond to the challenge to dominance started by the new upstream technology.[11] An illustration of this 'incumbent reaction' is captured by the following law of motion for the cost curves:

$$\dot{w}_N = (-\gamma_N - Ie^{-\beta I})w_N \tag{4.13}$$

$$\dot{w}_E = -\gamma_E w_N \tag{4.14}$$

where the term $Ie^{-\beta I}$ indicates that besides the exogenous component γ_N the percentage decrease in upstream technology cost of N is function also of the specific downstream application, and $\beta > 1$ is a parameter. The higher in the ranking a downstream sector is, the higher its potential cost reduction, but also the stronger the reaction of the established technology. Eventually, the potential effect and the reaction effect interact, generating a bell–shaped function. Dividing by w_j we obtain the percentage changes and thus the equation for $\dot{\omega}(I)$, yielding $\dot{\omega}(I) = \gamma_E - \gamma_N - Ie^{-\beta I}$.

Plugging the expression for $\dot{\omega}(I)$ just derived into 4.12 we find the new law of motion for I_e:

$$\frac{\partial I_e}{\partial t} \equiv \dot{I}_e = I_e(\epsilon_{I_e,\omega}\epsilon_{I_e,\zeta}) \left[(\theta_N(1 - I_e) - \theta_E(I_e)) + (\gamma_N + Ie^{-\beta I} - \gamma_E)\right] \tag{4.15}$$

[11] An alternative way to is to assume that network effects have decreasing returns, so that increasing adoption rates lead to further adoption, however at a slower pace.

In this case, the more N gains purposes, so I_e shifts to the right, the more ω increases its convexity. Depending on the elasticity of ω, the response of the established technology can lead to two structural equilibria (as shown in Figure 4.5), the leftmost being locally stable and the rightmost being unstable.

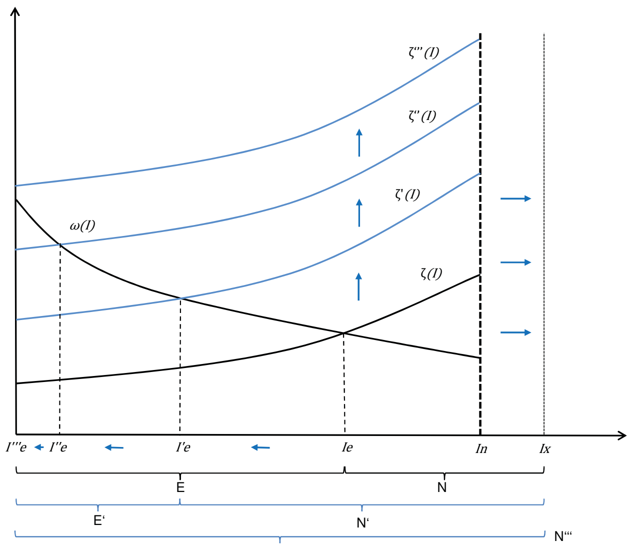

Figure 4.4: Dynamics of the Ricardian model — acquired pervasiveness of technology N

Note: the chart shows the dynamics of the model when $\dot{I}_e$ is affected by network effects operating on the $\zeta(I)$ function. The equilibrium is identified when $I_e = 0$ — meaning that the whole downstream market is served by the new upstream technology.

4.4 Conclusion

In this paper, we generalized the theory of GPTs to a theory of upstream technological competition for a downstream market of heterogeneous potential applications. To describe our phenomenon of interest, we recombined contributions belonging to different strands of literature: market connectivity, GPTs, economic development, and technology evolution. We defined a 'purposes acquisition' process as the dynamics leading a technology developed to deploy specific functions or to solve specific problems to identify fur-

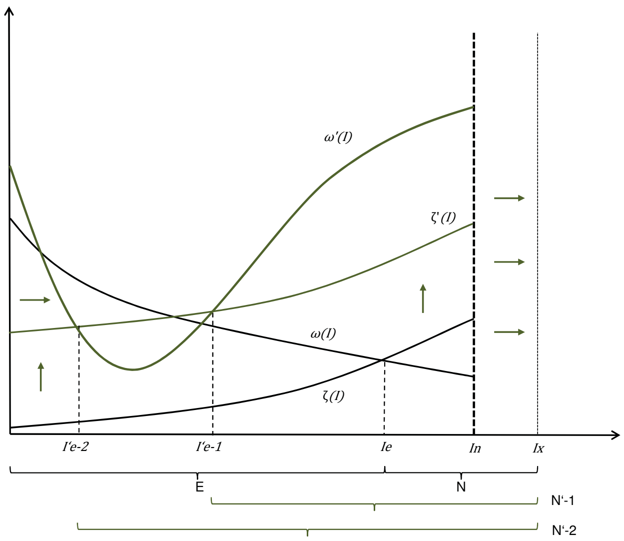

Figure 4.5: Dynamics of the Ricardian model — multiple equilibria

Note: the chart shows the dynamics when the established technology 'strikes back' acting on $\omega(I)$, but in a heterogeneous way, function of the downstream continuum. Two equilibria are identified.

ther purposes and uses than the ones the technology was originally planned or designed for.

We applied a simplified version of the Ricardian model of international specialization (Dornbusch et al., 1977) to a context of industries connected in a hierarchical (vertical) relation. In order to highlight the role different factors play in the competition for the downstream market, we kept a distinction between technological and economic explanatory variables. The model, notwithstanding its basic setting and the fact that it does not explicitly formalize the endogenous determination of payoffs, is useful to shift the focus of analysis towards relative (gap), rather than absolute dimensions. Learning mechanisms and feedbacks, as well as policy interventions, can be taken into account in a stylized way as comparative statics of the basic setting of the model. Also, it is showed that in the case featuring three upstream technologies the many possible specialization patterns that can occur in an economy with upstream-downstream linkages may lead to technological pervasiveness, to technological co–existence, and to failures, with potential GPTs that remain confined in downstream market niches.

From a critical viewpoint, it is possible to argue that while the paper claims that no GPT is foreseeable in advance, the model implicitly assigns the status of latent GPTs to the upstream technologies, therefore falling again in the a 'priori assumption' fallacy of GPT theories. On the one hand, such critique rightly points at a limitation of the paper; on the other hand, the main purpose of this study was to show how potential GPTs can fail to become GPTs given that to acquire purposes is not a trivial process but the result of technological competition in upstream markets. The model describes such process by offering a view based on comparative advantage and avoiding assuming which GPT dominates the market in equilibrium; this is a novel contribution that complements the existing literature.

Another critique has to do with the possibility to define a relative usefulness curve. Given the deep uncertainty characterizing new technologies, one can reasonably posit that some downstream industries have not just an imprecise valuation of the possible uses of upstream technologies, but that they do not have valuation at all, because the uses of the new upstream technology are not even considered among the possible states of the world. This remark, being certainly well taken, does not change the fact that downstream industries can always be ranked according to the relative benefit they expect from the new upstream technology. In case of deep uncertainty, the value of w_N will be 0 and the function $\zeta(I)$ in correspondence to those industries will lay on the horizontal axis.

From an evolutionary economics point of view, the model represents the competition for downstream market shares (where shares are the fraction of applications served by an upstream technology out of the total downstream market existing application). In this sense, it shares some features with the replicator dynamics model of Schumpeterian competition for the market (Metcalfe, 1994).

For what concerns the extensions of the model, candidates are the introduction of stochasticity and a through derivation of endogenous dynamics. Both extensions go in the direction to explain specialization patterns as a 'self–discovery' process in presence of uncertainty and learning (Hausmann and Rodrik, 2003). Another possible extension relates technological competition in vertically related markets to Industry Life Cycles theories (Klepper, 1996). Finally, the empirical side of this research could be developed starting from decomposition exercises (Cantner and Krüger, 2008) to be extended to vertically related industries.

In sum, the main contributions of the paper are i) the framing of GPT theory into a more general analysis of vertically-related industries; ii) the modeling of a downstream market specialization when alternative upstream technologies are available and the dynamic of GPT emergence, from a 'specific' (niche) upstream industry to a pervasive one; iii) the resulting possibility for potential GPTs to fail to diffuse into the economy. To conclude, the process leading to acquired purposes is not supposed to automatically lead to the establishment of a pervasive GPT. Rather, the establishment of GPTs it is closer to an emergent phenomenon, with multiple possible (even if not equally possible) outcomes. Besides the technical features of technologies, it is the task and the responsibility of economic agents and policy–makers to determine which alternative specialization path is to be taken.

Chapter 5

Replicator Dynamics in Value Chains: Explaining Some Puzzles of Market Selection

5.1 Introduction

This Chapter studies the role of firms integration into value chains (hereinafter VC) on competitive market selection. Under the integration into value chains we mean that the performance of a firm is not only dependent on its own performance (e.g., productivity, profitability) but also on that of its partners with whom it is vertically related to produce a finished good for consumers.[1] Within a value chain, trust and division of labor among supplier and user industries is enhanced, while flexibility in the choice of partners is lower compared to a pure arm–lenght market transaction, where firm can compete for the best suppliers. The idea that accounting for value chain

[1] In the Chapter, we use the term fitness rather then performance to indicate the abstract 'goodness' of the unit of analysis with respect to its reference group (competitors) or environment (industry, market) to keep consistency with the literature on the replicator dynamics.

relations may shed some light on competition dynamics extends and may be at odds with the original stylized model of market selection developed by Metcalfe (1994) (also known as 'replicator dynamics model')[2].

In the classic replicator dynamics model, vertical relationships among firms can be implicitly considered only as long as their effect is homogeneous across the firms acting in the focal market. The differential performance of firms is therefore only attributable to different idiosyncratic competences and abilities. Contrarywise, we argue that this connection can have a decisive influence on firms' success or failure in market selection, given that value chains can be highly heterogeneous due to suppliers' different costs structures and product qualities, and to a certain degree of stickyness of the connections. The importance of firms' vertical relations is confirmed not only by marketing research reporting that the value of business–to–business (B2B) contracts in many industries is exceeding the one from the business–to–consumer (B2C),[3] but also by numerous studies pointing to the fact that in the modern economy the degree of specialization and division of labor is constantly increasing and instead of conducting the entire production cycle in–house, many stages get outsourced to firms specializing in certain tasks and phases of the production process, due to their higher productivity or possess of specific resources and capabilities. An important feature of that vertical relationships, however, is that firms collaborating on a long term basis adjust their production process to each other so that switching one's partner becomes a very (if not prohibitively) costly issue. As a result, over time a firm may get locked into cooperation with less fit partners, which has a direct impact on the firm's performance and market share development.

The principle of reallocation of market shares from less efficient firms to their more fit competitors is the key principle of selection–based theories (Friedman, 1953; Foster et al., 2008), which also play an important role in the evolutionary economics literature (Nelson and Winter, 1982). However,

[2] An alternative derivation of the replicator dynamics used by economics scholars can be found in Schuster and Sigmund (1983). See Silverberg (1997) for a discussion.

[3] The major reason for this is that in a typical supply value chain there are many B2B transactions involving sub–components or raw materials, and only one B2C transaction, namely sale of the finished good to the end customer. For example, a computer manufacturer makes several B2B transactions such as buying microchips, different cables, cooler, which producers in their turn buy, e.g., nanometer transistors, rubber, plastic and metal.

when it comes to empirical testing of the theory, evidence of that principle is at best mixed and at worst contradictory (Cantner, 2014). A first set of explanations for this set of results ranges from the choice of not appropriate variables for firm performance (fitness) to not clearly demarcated units and populations under analysis (firms vs products, industries vs markets/sub–markets). Other explanations refer to neglected fitness relevant components (such as sunk costs, see Hölzl (2015)) or — as in this Chapter — to the exclusion of factors relevant for market share changes such as a firm's integration into a value chain. The topic of vertical relations and value chains is usually studied through the lenses of transaction–cost theories, in order to assess advantages and disadvantages of integration and complex contractual arrangements (Bresnahan and Levin, 2012). By linking the literature on vertical relations and market selection, this Chapter fills a relevant gap and is the first, to our knowledge, to explicitly model vertical relations as determinants of selection dynamics.

Dealing with the market performance of firms integrated in the value chain requires to take into account how the market performance of the downstream firm influences the market performance of the upstream firm and vice–versa. To simplify the issue at stake, in this study we assume that the number of output units of the downstream firm entirely determines the number of output units of the upstream firm. This strict relation implies that capacity expansion (or reduction) of the upstream firm is not only dependent on this firm success in its own market but also on the success of the downstream firm in her market. At the limit, such an assumption implies that the replicator dynamics is factually at work only in the final good market, while upstream firms just respond to downstream market shares reallocation. This simplification becomes useful when we assess through decomposition methods the effects on selection due to downstream competition and innovation dynamics in all the layers of the value chain. By applying simulation techniques we are interested under which constellation of value chain relationships the usually expected outcome of the replicator dynamics is not showing up or even reversed in its results.

The Chapter proceeds as follows. The next section provides a literature review together with hypotheses to be tested. Section 5.3 describes the model of the replicator dynamics into the value chain context while in Section 5.4 its main results are summarized. Section 5.5 discusses the model's implications and concludes.

5.2 Literature Review and Hypotheses

In what follows we review the literature whose main focus is the empirical study of market selection and market shares reallocation. In a nutshell, the theoretical prediction of the replicator dynamics goes in line with the Darwinian 'survival of the fittest' principle: ideally, a firm with a higher (lower) fitness than the (share–weighted) average of the population increases (decreases) its market share and drives further the selection dynamics by affecting the level of the share–weighted average fitness in the following periods, unless negative feedbacks dampen the dynamics.

Empirically, the literature on market shares reallocation and selection is strongly related to that on productivity dynamics, especially at the micro level. The latter has been boosted by the recent availability of firm and establishment level data, which start to shed some light on the determinants of firm's heterogeneity and characteristics (e.g. productivity and profitability) dispersion (Bartelsman, 2010). As a first approximation, we can distinguish between studies grounded on Empirical Industrial Organization (EIO) on the one hand and Neo–Schumpeterian theories on the other hand; however, the papers classified in this rough taxonomy often share a consistent part of methodological premises.

The first strand of research — that studying market selection from an EIO perspective — descends from models of industry 'equilibrium evolution' (such as Jovanovic (1982) and Hopenhayn (1992)) and operates a 'dissection' of aggregate productivity (usually at the industry level) by decomposing it in more fundamental components, either in a static or dynamic way. Static decompositions follow from the seminal exercise of Olley and Pakes (1996), that separates the first moment of the productivity distribution (the non–weighted average productivity) from a covariance term, measuring the distortion provoked by the reallocation of shares from less to more productive firms. Maliranta and Määttänen (2015) extend the static Olley–Pakes decomposition to account for different categories of firms (stayers, entrants, exiters and visitors). Dynamic decompositions usually build upon the contribution of Baily and Campbell (1992) to explain changes in aggregate productivity, rather than its level. Griliches and Regev (1995) and Foster et al. (2001) extend the dynamic decomposition framework to account for entry and exit (the two methods differ only with respect to the benchmark productivity used to calculate the change). Dynamic decompositions distinguish between two main sources of productivity change: a *within component*, usually interpreted in terms of firm–specific learning, and a *between* (plus covariance) *component*, capturing the competition and reallocation (selection) dynamics. A combination of the static and dynamic decomposition is derived in Melitz and Polanec (2015), where a dynamic Olley–Pakes decomposition with entry and exit is considered in order to explain aggregate productivity changes while maintaining the distributional approach of the static methods. From the theoretical side, Foster et al. (2008) discuss the nature of selection on productivity and profitability by building and estimating a model in which the selection dynamics is determined by 'physical' productivity, prices, and demand shocks. In general, the assessment of market selection in the literature described above is what we label an 'indirect' one, since the replicator dynamics is not tested explicitly but inferred through the sign and magnitude of the between effect.

The Neo–Schumpeterian literature addresses as well the issues of productivity dispersion, firms heterogeneity and the interaction between learning and selection. However, these studies rely more explicitly on the evolutionary assumptions of the replicator dynamics model; the idea is to test Schumpeter's concept of competition *for the market*, rather than competition *in the market*. Again using indirect methods (namely the Foster et al. (2001) decomposition), Cantner and Krüger (2008) and Krüger (2014) find for German manufacturing firms over the period 1981–1998 a weak tendency that above–average productivity firms are selected in favor of below–average productivity firms — this supporting a market selection process in line with the replicator dynamics. By splitting the sample in two periods (before and after German reunification), Cantner and Krüger (2008) are able to highlight the stronger effect of market reallocation in the period 1990–1998, interpreted as a consequences of increased competition due to the reunification shock. In a follow–up study by Krüger (2014), however, these results could not be confirmed. Similar results have been also obtained by Bottazzi et al. (2008) and Coad (2007), where it is the within component — that is, learning — that mainly drives productivity growth. In general, Metcalfe and Ramlogan (2006) take a critical view to the decomposition exercises, considering them on the one hand useful to uncover the dynamics behind the restless nature of capitalism, but on the other hand sensible to the assumptions on the 'shapes' of the within and between components. They call for a sound theory of the interplay between innovation and market reallocation, to be constructed above these 'evolutionary accounting' methods.

Beyond the indirect approaches, some studies attempted a direct operationalization of the replicator dynamics. In particular, Metcalfe and Calderini (2000) measured the speed of selection, a specific parameter in the replicator equation, for a dataset of the Italian steel industry. They cannot convincingly show that an evolutionary process according to replicator dynamics is at work. More recently, Dosi et al. (2015) have enriched the picture on the strength of selection combining direct and indirect approaches. In their analysis they conduct a decomposition exercise using firm level productivity data for four countries (US, France, Germany and the UK), and also estimate directly the speed of selection for different industries in each country. For both exercises, the results are rather mixed, not supporting the standard replicator model. A major reason is that an industry is not a market but a collection of markets, the firms are multi–product, and the fitness variable is entirely supply–side determined, in particular, in terms of unit costs of production. Cantner et al. (2012) take up this criticism and analyze the rather narrowly defined market for compact cars in Germany using a relative quality–price ratio, obtained aggregating information over four main product characteristics and prices, as proxy for a firm fitness. They find rather compelling evidence for the selection effect working in the expected direction.

Now, the replicator dynamics suggests that a firm's market share change is positively related to that firms relative performance in production; hence a firm that compared to the other firms shows an above (below) average production performance is expected to increase (decrease) her market share. That mechanism at work requires a market with one price (and market clearing) and profits (or losses) being used to invest into capacity expansion (or for disinvestment, respectively). Market shares have to develop accordingly. With a firm's integration into value chains this mechanism may not work properly. A first issue is the law of one price: With long–term relationships special prices can be negotiated, leading to heterogeneity in prices. A second issue, related to the former, is that vertically related firms may cooperate and hence investment is done together. A third issue is related to the demand for an intermediate product: if the downstream firm performs successfully, it will increase its productive capacity and by this increase the demand for the intermediate product; hence, the intermediate supplier, even when performing below average in its own market, will face this increased demand, provide the necessary expansion in capacity and experience a growing market share. All these constellations are at odds with the ideal selection mechanism and may lead to the observation that in a specific market a below average performing firm is able to increase market shares because her very well performing partners along the value chain are able and willing to pay higher intermediate product prices or are engaged in an investment cooperation with that firm or demand more intermediate products.

In the following model we just argue in terms of the output relationships between firms along a value chain and leave aside the features of differentiated prices and cooperation in investment. To analyze this framework, we suggest the following **hypotheses**:

1. In case all firms of a value chain hold in their own market the same production performance position, then market selection in each market should follow the principle of replicator dynamics.

2. In case of downstream firms in their own market show a higher rank in terms of production performance than their partners in upstream markets, the principle of replicator dynamics does not necessarily hold in upstream markets.

5.3 Basic Model

We start by clarifying the variables and notation we use in this study. This first means to determine which is the choosen proxy for the fitness variable. As it is clear from the literature review, any performance indicator may serve the scope; usually more or less elaborated versions of the (labor or total factor) productivity, product quality or costs are used. In order to ease the comparison and to highlight our contribution with respect to other modeling exercises (e.g. Mazzucato (1998)), we first define firm's *total unit cost* C^i_m (for each firm i on value chain layer m). Being the result of a successive transfer of intermediate goods from layer to layer, the unit price of layer $m-1$ becomes part of the total unit cost of layer m, to which its own *layer–specific unit cost* has to be added. In general, the total unit cost for each layer can be decomposed as $C^i_m = p^i_{m-1} + c^i_m$, where p^i_{m-1} is the price of the intermediate good of the upstream layer $m-1$ and c^i_m is the layer–specific unit cost. The price of the upstream intermediate good $m-1$ can be expressed as $p^i_{m-1} = p^i_{m-2} + c^i_{m-1}(1+\phi)$, where ϕ is a constant markup, calculated on the 'value added' rather than on the cost of all supplies. Hence, for any value chain, for the first layer (layer one) C^i and c^i are assumed to be identical ($C^i_1 = c^i_1$), as the firm has only its own cost of extracting primary resources of production; for the second layer of the value chain, the total unit cost becomes $C^j_2 = c^j_2 + p^j_1 = c^j_2 + c^j_1(1+\phi)$ and so on until for the Mth layer of production, $C^j_M = c^j_M + p^j_{M-1} = c^j_M + \sum_{m=1}^{M-1} c^j_m(1+\phi)$.

Last layer total unit cost C^i_M, that equals the whole value chain unit cost, is our fitness variable (equations (5.1) to (5.4) in what follows explain why we use only C^i_M as fitness, assuming that shares dynamics in all the upstream markets follow the behavior of the last — downstream — market). We sometimes also refer to this variable as *aggregate fitness*. Hereinafter, whenever not differently specified, the use of the term total unit cost refers to C^i_M, the last layer (and the whole value chain) cost.

Further assumptions:

1. there are M (let us start for simplicity with three) vertically integrated

markets, where on each market N_m firms are operating. One can refer to those three layers as 'suppliers', 'manufacturers' and 'distributors';

2. no firm can produce a finished good alone, but only in cooperation with firms in other markets. Thus, we leave out the possibility of vertical integration with one single firm present on more than one layer (market);

3. we abstract from entry and exit behavior to isolate the effect of selection dynamics ($\forall m = 1, \ldots, M \;\; N_m =$ constant);

4. for the sake of simplicity, we also ignore sources of uncertainty for value chains such as demand (volume and product specification), process (e.g., machine downtime and transportation reliability) and supply (e.g., delivery reliability) described in detail in Strader et al. (1998). Instead, we assume perfect collection and sharing of information between supply chain members, which results in no inventories necessary and order fulfillment cycle time being minimized. Such a perfect management of lead–time in turn presents a barrier for value chain members to switch their partners, since tuning of this management is costly in terms of time and resources. In absence of any friction or asymmetry, this assumption may create the conditions for the establishment of vertically–integrated firms. However, this possibility is ruled out by assumption two: the impossibility of integration may be anyway justified with arguments related to product complexity, specialization and division of labor.

5. also for simplicity, goods on each market (including the market of finished good M) are homogeneous: market dynamics is only driven by firms' differential fitness;

6. firms on all M layers seek to earn profit. Thus, on all M layers profit margin per unit of output firms charge is fixed (parameter $\phi = 0.1 = \frac{p_m^i - c_m^i}{c_m^i}$ (10%)), where p indicates the price and c_m^i the firm and layer specific cost. In principle, one could abandon that parameter. However, since firms in our model implicitly conduct cost–reducing R&D, we consider positive profits in order to add realism to the model. One can later investigate the role played by different markup settings;

7. another standard assumption from replicator model adopted in this study is the investment in capacity extension: whenever a firm makes profits by selling its output at a price above its costs, a portion of the profit is invested in increasing its capacity $g^i_m = \lambda(p^i_m - c^i_m) = \frac{y^{i,t}_m - y^{i,t-1}_m}{y^i_m}$, where g is the firm growth rate, which in turn is defined as the ratio of its output y rate of change over its total production. λ indicates the (constant) share of investment out of unit profits; unless specified differently, we set the parameter $\lambda = 0.01$.

From the replicator model (Metcalfe, 1994) we know that market share $s^i_m = \frac{y^i_m}{y_m}$ of firm i on market m changes according to the following selection equation, where the term f stands for 'fitness':

$$\Delta s^{i,t} = s^{i,t} - s^{i,t-1} = s^{i,t}\lambda(f^{i,t-1} - \bar{f}^{t-1}). \tag{5.1}$$

As anticipated in the introduction, given that we consider a naive value chain structure with only one connection in each layer and no other markets (or firms) connected to those considered here, one can reasonably argue that the unit output of firm j in the final layer must be equal to its supplier's one in each preceding layer $y^i_M = y^i_{M-1} = ... = y^i_1$, while the total unit output of market M is equal to the preceding ones: $y_M = y_{M-1} = ... = y_1$. As a consequence, the following equalities must hold:

$$\Delta y_M = \Delta y_{M-1} = \cdots = \Delta y_1. \tag{5.2}$$

i.e. aggregate changes in outputs on all markets are equal.

$$\Delta y^j_M = \Delta y^j_{M-1} = \cdots = \Delta y^j_1. \tag{5.3}$$

i.e. changes in outputs of all firms on different layers matched into one value chain are also equal. As a result, on can state that also changes in market share of all firms from different layers related to one value chain are also the same:

$$\Delta s_M^j = \Delta s_{M-1}^j = \cdots = \Delta s_1^j. \tag{5.4}$$

5.4 Results

In the following we explore the behavior of the model under different scenarios summarizing our results in five propositions.

5.4.1 Random Value Chain Matching With No Innovation

We consider two contrasting scenarios: in the first one, firms located on each market m have their layer–specific unit cost drawn in a way that each downstream firm surpasses the next one by the same amount (e.g., 1, 1.5, 2,...); the firms integrated in a value chain are matched according to their fitness: the most fit firm in market M with the most fit ones in market $M-1$, $M-2$ etc. and the other way around. In the second scenario, firms having their fitness drawn the same way as in the first scenario are matched randomly — some less fit firms may be matched with more fit ones (see Figure 5.1). To focus on the selection dynamics driven by VC relations, we assign to all the firms the same initial market share.

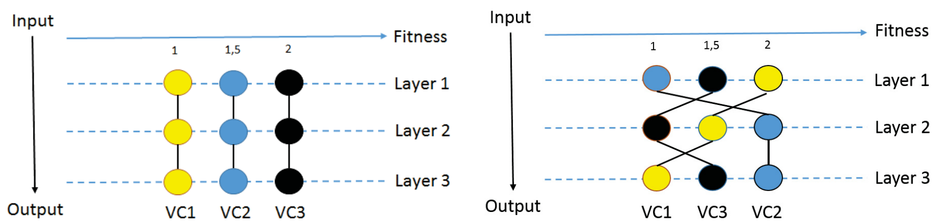

Figure 5.1: Firms' ordered and random matching in value chains

Note: The left panel corresponds to ordered matching, while the right one to random matching.

Let us denote the most fit firm in each layer with index a, the second most fit with b and (for the simplified case of three firms only) the least fit firm with c. Hence, in the ordered matching we have all a firms linked together (having total unit cost C_M^a), while in the random matching — they are randomly distributed in different VCs. Therefore, in the ordered matching scenario (benchmark) the most fit firm in each layer increases its market share according to equation (5.1). In particular,

$$\Delta s_M^{a,t} = s^{a,t} - s^{a,t-1} = s_M^{a,t}\lambda(\bar{C}_M^{t-1} - C_M^{a,t-1}). \tag{5.5}$$

The difference between (5.5) and (5.1) is that the 'monopolization' takes place for the VC case even faster since

$$\begin{aligned} C_M^a - C_M^b =& c_M^a + \sum_{m=1}^{M-1} c_m^a(1+\phi) - c_M^b - \sum_{m=1}^{M-1} c_m^b(1+\phi) = \\ =& c_M^a - c_M^b + (1+\phi)\left(\sum_{m=1}^{M-1} c_m^a - \sum_{m=1}^{M-1} c_m^b\right) > c_M^a - c_M^b. \end{aligned} \tag{5.6}$$

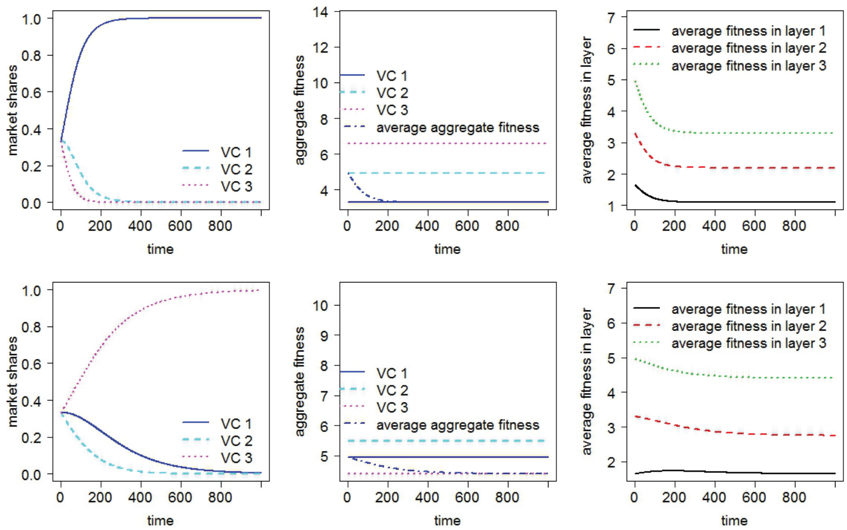

Figure 5.2: Dynamics with ordered and random matching

Note: The upper panel corresponds to ordered matching, while the lower one to random matching. $M = 3$ and $N = 3$.

In the random matching scenario, in contrast, the monopolization takes place potentially slower since in each layer firms with different fitness are matched. Eventually, one of the VCs certainly dominates the other one (as long as its total unit cost is lower), but this has a (negative) side effect in a sense of a less fit firm in one (or more than one layer) dominating with its market share its counter–partners. To illustrate that, consider Figure 5.2.

The leftmost charts in the upper and lower panels display the differences in the speed of market reallocation for ordered and random matching, respectively; the overall selection dynamics among the three different value chains looks rather similar, except that the final winner is different. The mid charts show VC–wise the corresponding dynamics with respect to changes in the average total unit costs $\bar{C}^j_M$.[4] Finally, the rightmost charts in Figure 5.2 show layer–wise the development on each of the three markets. In case of ordered matching, the dominating VC1 is built up by the dominating and hence best firms in *each* market (layer); these firms drive down the average $\bar{C}^j$ in each layer to the level of VC1, just in line with replicator dynamics. Also in the random matching case the average $\bar{C}^j_m$ in each layer approaches that of the prevailing VC — in this case VC3. However, there the average fitness approached in each layer is not necessarily the 'best', as it should happen when the replicator dynamics holds. This is more evident when looking at the average fitness in layer 1, that increases in the first 200 simulation periods and then just returns to its original level. The integration into a value chain and the piling up of total unit costs as fitness indicator produces a dynamics that violates that standard replicator predictions. We name such violation a *regressive development*.

Analytically this can be supported in the following way. Remember that $\bar{C}_m = \sum_{n=1}^{N} s^n C^n_m$ and given that in our particular case (through a random event) the second least fit firm from the first and third layers have been matched with the most fit firm in layer **two**, the total unit cost of that value chain (VC3 on the bottom mid chart of Figure 5.2) is lowest, and hence, it is merely a question of time when this value chain and effectively not fittest firms in layers one and three will dominate the market (see equation (5.5)). Hence, results stated above support our hypotheses from Section 5.2 and allow to formulate the following propositions:

Proposition 1. *A firm with a fitness below the average of the market it is operating in may dominate it if it is integrated with highly fit partners from other layers, making the overall fitness of the value chain highest on the final end consumer market (layer M).*

[4]Note that so far no innovation (in the sense of autonomous cost improvements by firms) is allowed and only the market share reallocation dynamics, by affecting the market–weighted average fitness, is driving the aggregate behavior of the model.

Proposition 2. *The average fitness in upstream layers of a value chain can increase rather than decrease over time if upstream firms that are less fit than the average of the market they are operating in are linked to highly fit partners in downstream layers of the value chain. This dynamics violates the predictions of the standard replicator dynamics model and can be considered a* regressive development of market selection *driven by value chain relations.*

Furthermore, we would like to stress that the famous *Fisher's principle*, stating that the change in average fitness, and hence the speed of market shares reallocation, in a population of competing firms is proportional to the variance in fitness, is also valid to this model of firms matched into value chains.[5] In particular, from Figure 5.2 one can see that the difference in aggregate fitness between value chains in case of ordered matching is higher (since all most fit firms are matched together against all least fit firms), and as a result, average total unit cost improvement and market share reallocation are taking place much faster. A similar effect can be also obtained under the following three conditions:

1. larger number of value chain layers M, but only for ordered matching. If one increases the number of layers M from three to, e.g., ten, then for ordered matching the difference in aggregate fitness between the value chains measured by total unit costs C_M^j will increase and domination of one value chain over other competitor chains will take place faster (see Figure 5.13 in the Appendix).[6] This is because the term $\left(\sum_{m=1}^{M-1} C_m^a - \sum_{m=1}^{M-1} C_m^b\right)$ is increasing with every new layer of a value chain. For random matching scenario, in contrast, no difference should be obtained, since the value chains are matched randomly and on average shall contain for different M the same portion of more (a)

[5]This strictly holds for the aggregate fitness (total unit cost) of VCs (since competition on the end consumer market defines market share reallocation, $\Delta\bar{C} \sim \sigma^2(C^j)$), but also — indirectly — for each market layer (since the variance in firm's fitness on each of the layers contributes to the respective variance of the value chains. For each single layer this, however, may not necessarily hold since even though there is a low variance in fitness, e.g., on layer one, the market share reallocation may still be high and *equal in speed for all layers* due to high variance in fitness on other layers.

[6]Note here that we keep the variance in unit cost fixed in each layer, and increasing M naturally leads to larger differences between value chains.

or less (c) fit agents:

$$E[C^j] = \frac{c_M^a}{N} + \frac{c_M^b}{N} + \frac{c_M^c}{N} + \sum_{m=1}^{M-1} \left(\frac{c_m^a}{N} + \frac{c_m^b}{N} + \frac{c_m^c}{N} \right) (1+\phi). \quad (5.7)$$

Therefore, any difference in speed of market reallocation between bottom leftmost charts in Figures 5.2-5.13 is due to a random event (particular random VC matching) and not to any objective criterion.

2. larger profit margin ϕ since it increases the variance in fitness on the final layer M (see 5.6–5.7) similarly affecting the ordered and random matching scenarios (Figure 5.14 in the Appendix).

3. larger variance in fitness between firms on any layer. Increasing the variance in fitness between firms on any layer $(\sigma^m)^2 = \sum_{n=1}^{N} \left(C_m^n - \bar{C} \right)$ in our model, one increases the differences in expected total unit costs between the value chains, which automatically leads to faster market reallocation process. This result holds for both, ordered and random matching scenarios (Figure 5.15 in the Appendix).

5.4.2 Random Value Chain Matching With Innovation

In this section we extend the model by allowing firms to endogenously improve their specific fitness (that is, to reduce their layer–specific unit costs) through innovative activities.

The selection dynamics becomes in this way affected by two different and interacting forces acting on two different levels: on the one hand, the market reallocation based on the VC–dependent fitness (that is, on the total unit cost variable); on the other hand, firms' innovation activities resulting in performance improvements based on each specific layer (market). The distinction of the level of analysis at which selection and innovation operate is justified by the fact that it captures the real–world behavior of firms. In fact, in each layer firms compete on the basis of their total cost of production — that is function also of all the prices payed on each stage for intermediate goods and supplies — but take efforts in order to improve their own idiosyncratic processes and products. In a nutshell, we include now in the model both the between (competition) effect and the within (learning/innovation) one. Our main contribution is to condition the reallocation on the VC structure, making the case for the replicator dynamics to work in unexpected ways. In what follows, we adopt three alternative specifications of cost–reducing innovation process: with *constant*, *decreasing* and *increasing returns to scale* (henceforth, CRS, DRS and IRS, respectively). Following Mazzucato (1998), this is done by setting

$$c_m^{j,t+1} = c_m^{j,t}\,(1-\gamma) \qquad \text{for constant returns} \tag{5.8}$$
$$c_m^{j,t+1} = c_m^{j,t}\left(1-\gamma(1-s_m^{j,t})\right) \qquad \text{for decreasing returns} \tag{5.9}$$
$$c_m^{j,t+1} = c_m^{j,t}\left(1-\gamma s_m^{j,t}\right) \qquad \text{for increasing returns.} \tag{5.10}$$

All these specification of technological progress are function of an exogenous rate of technical improvement (cost reduction) γ reinforced, dampened or neutrally–affected by firm size (measured by the market share). The possibility of cost reduction with constant returns to scale, as expected in accordance with the standard replicator model, creates the possibility of more than one value chain staying on the market (see leftmost charts in Figure 5.3).

Since in the ordered matching, the difference in total VC unit costs between the value chains is originally larger, the dominating value chain achieves a higher market share than in the case of random matching. The fact that the less fit firm obtains an advantage through linkages with strong partners in other layers can also be seen from Figure 5.3. The dynamics of the average fitness in each layer, as shown in the rightmost charts, tends to be similar in the ordered and in the random matching. However, its interpretation becomes less trivial. In fact, the reduction in average total unit costs in each layer can be driven by two dynamics: if the initially fittest firm gains market shares, then average layer fitness decreases. On the other hand, even if a non–fittest firm, linked with fitter firms in other layers, gains market shares, the average layer's fitness may decrease instead of decreasing if the magnitude of cost–reducing innovative activities prevails over the increasing weight of the non–fittest firm's cost in the calculation of the average layer fitness. In other words, the within and the between effects may compensate each other and hide the tendency of market selection to work in the 'wrong way'. In order to disentagle these two related dynamics affecting selection, we turn to a decomposition exercise.

We consider the following decomposition of the change in market weighted average total unit cost in layer m:

$$\begin{aligned}
\Delta\bar{C}_m^t =&\bar{C}_m^t - \bar{C}_m^{t-1} = \sum_i s_m^{i,t}C_m^{i,t} - \sum_i s_m^{i,t-1}C_m^{i,t-1} = \\
&= \sum_i \left(s_m^{i,t}C_m^{i,t} - s_m^{i,t-1}C_m^{i,t-1}\right) = \sum_i \left((s_m^{i,t-1} + \Delta s_m^{i,t})(C_m^{i,t-1} + \Delta C_m^{i,t}) - s_m^{i,t-1}C_m^{i,t-1}\right) = \\
&= \sum_i \left(s_m^{i,t-1}C_m^{i,t-1} + s_m^{i,t-1}\Delta C_m^{i,t} + \Delta s_m^{i,t}C_m^{i,t-1} + \Delta s_m^{i,t}\Delta C_m^{i,t} - s_m^{i,t-1}C_m^{i,t-1}\right) = \\
&= \sum_i s_m^{i,t-1}\Delta C_m^{i,t} + \sum_i \Delta s_m^{i,t}C_m^{i,t-1} + \sum_i \Delta s_m^{i,t}\Delta C_m^{i,t} + 0 = \\
&= \sum_i s_m^{i,t-1}\Delta C_m^{i,t} + \sum_i \Delta s_m^{i,t}C_m^{i,t-1} + \sum_i \Delta s_m^{i,t}\Delta C_m^{i,t} + \sum_i \Delta s_m^{i,t}\bar{C}_m^{i,t-1} = \\
&= \sum_i s_m^{i,t-1}\Delta C_m^{i,t} + \sum_i \Delta s_m^{i,t}\left(C_m^{i,t-1} - \bar{C}_m^{i,t-1}\right) + \sum_i \Delta s_m^{i,t}\Delta C_m^{i,t}. \qquad (5.11)
\end{aligned}$$

Where any $\Delta C_m^{i,t} = \Delta \sum_{m=1}^{M-1} c_m^j(1+\phi) + \Delta c_m^{i,t}$, that is the total unit cost of a firm, changes as a result of innovation in all the suppliers' layers and in its own specific production process. The first term in equation (5.11) captures the within effect (the sum over all the individual firms cost changes each multiplied by the market share before the change in fitness), the second term — the between effect (the sum of market share changes weighted by the deviation of a firm's cost level from the market–weighted mean cost level of all firms — that is basically **the replicator term** we are most interested in), while the third term is the so–called covariance effect (which being negative indicates that the selection is faster than predicted by the replicator mechanism alone, while its positive value is associated with slower selection compared to the replicator dynamics mechanism (Cantner and Krüger, 2008)). The covariance component captures the dynamics returns to scale introduced by innovative activities. For the standard replicator dynamics to hold the second term (the between effect) has to be negative for *each* market, i.e. each firm being less productive than market average should decrease its market share.

The corresponding decompositions into the within, between and covariance effects are reported in Figure 5.4. Clearly, while in the ordered matching the between effect is consistently negative and of comparable magnitude with the within effect in all three layers, the pattern is very different for the random matching. In particular, the between effect becomes much smaller in absolute terms and turns to be positive in the layer one, indicating that in this market a firm integrated in a strong VC was increasing its market share although its fitness was below the market average. Hence, from the decomposition exercise it becomes clear that the replicator dynamics does not necessarily hold in markets that are vertically related (again supporting the hypotheses stated earlier).[7]

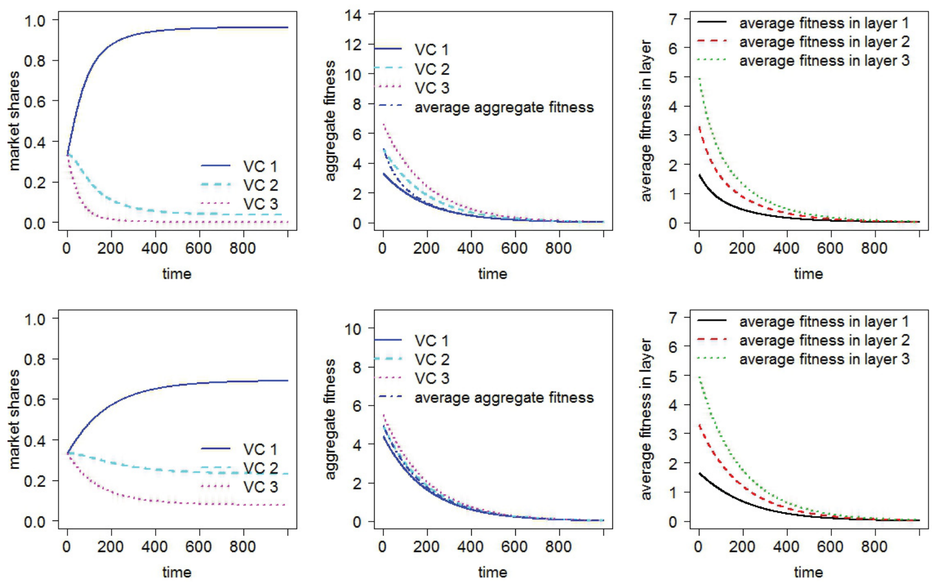

Figure 5.3: Dynamics with ordered and random matching and innovation with CRS

Note: The upper panel corresponds to ordered matching, while the lower to random matching. $M = 3$, $N = 3$ and $\gamma = 0.005$.

[7]Note that in the former exercise with no innovation the within and covariance effect are zero, as there is no change in layer–specific unit costs over time. The between effects however are present and also occasionally turn to be positive in one or the other layer in the random matching scenario.

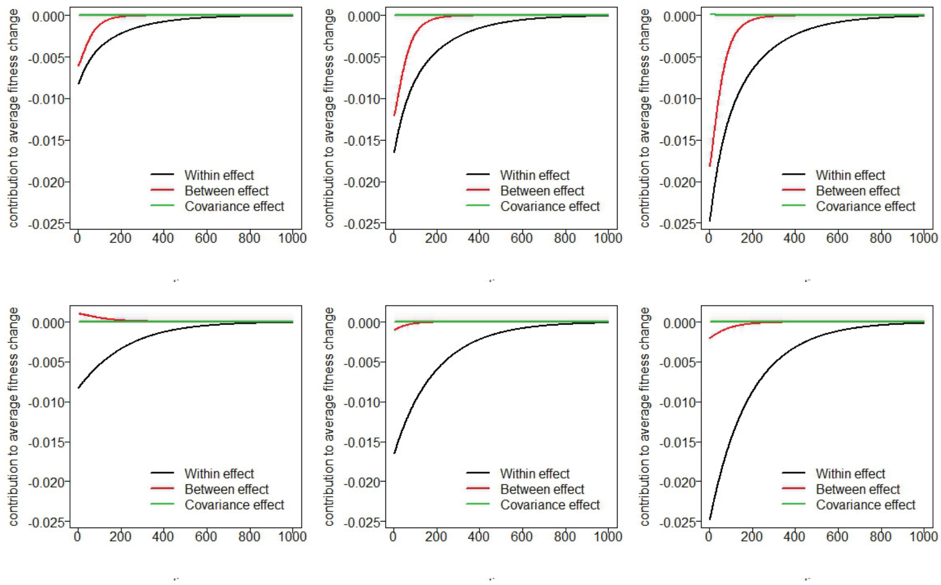

Figure 5.4: Decomposition of change in average unit cost with CRS

Note: The upper panel corresponds to ordered matching, while the lower to random matching. From the left to the right the markets (layers) 1, 2 and 3 are shown.

For decreasing returns to scale: Setting the rate of cost reduction to be inversely proportional to market share, one obtains a typical pattern of high volatility of market shares in the initial period. This volatility is (potentially) higher in the ordered matching, where the differences in fitness between the value chains are higher (Figure 5.5). The corresponding contribution of the within, between and covariance effects to the change in market weighted average fitness is presented in Figure 5.6. Again, the between effect is close to zero and occasionally turns positive in the random matching scenario, but not in the ordered matching one.

For increasing returns to scale: As it is typical for IRS, a random event (in terms of slightly lower layer–specific unit cost at the beginning of simulation) defines which of the value chains will dominate the others. Once firms start innovating, evolution of unit costs and market shares (at least for the leading VC) proceeds much faster than in the scenario with constant returns to scale (Figure 5.7). The process of market monopolization is taking place again faster in ordered matching as the initial advantage of the fittest value chain over its counterparts is larger. Similarly, the decomposition in the between, within and covariance effects demonstrates that in one of the layers (here layer one) the between effect deviates from the prediction, being positive in the first three hundred periods (Figure 5.8). One can conclude that also under IRS a less fit firm integrated in a superior VC gets an opportunity to improve its fitness rank to the level of the partners.

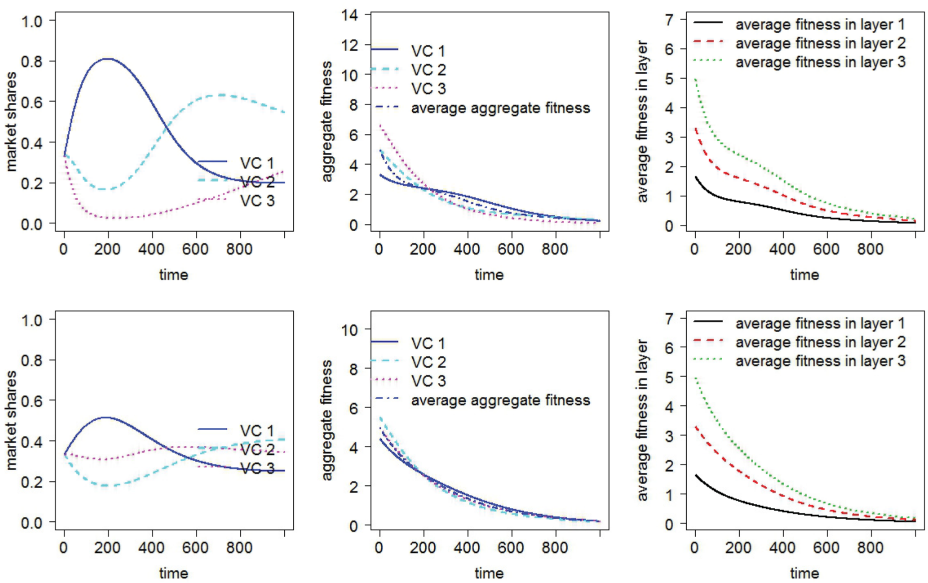

Figure 5.5: Dynamics with ordered and random matching and innovation with DRS

Note: The upper panel corresponds to ordered matching, while the lower to random matching. $M = 3$, $N = 3$ and $\gamma = 0.005$.

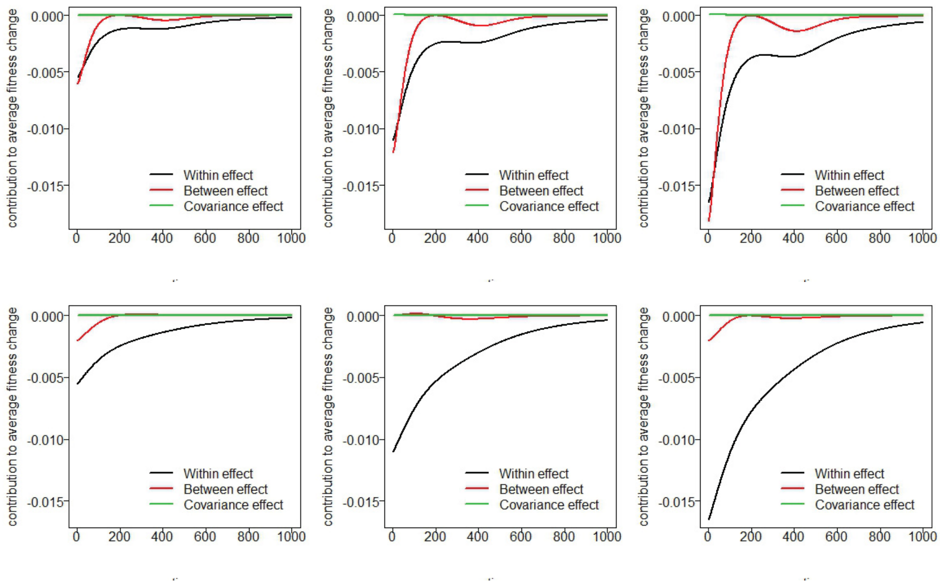

Figure 5.6: Decomposition of change in average unit cost with DRS

Note: The upper panel corresponds to ordered matching, while the lower to random matching. From the left to the right the markets (layers) 1, 2 and 3 are shown.

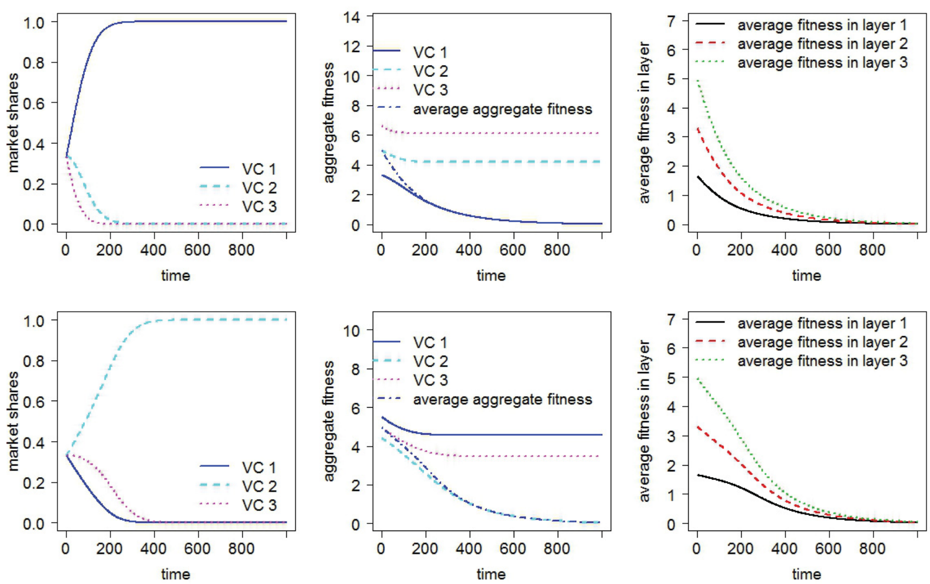

Figure 5.7: Dynamics with ordered and random matching and innovation with IRS

Note: The upper panel corresponds to ordered matching, while the lower to random matching. $M = 3$, $N = 3$ and $\gamma = 0.005$.

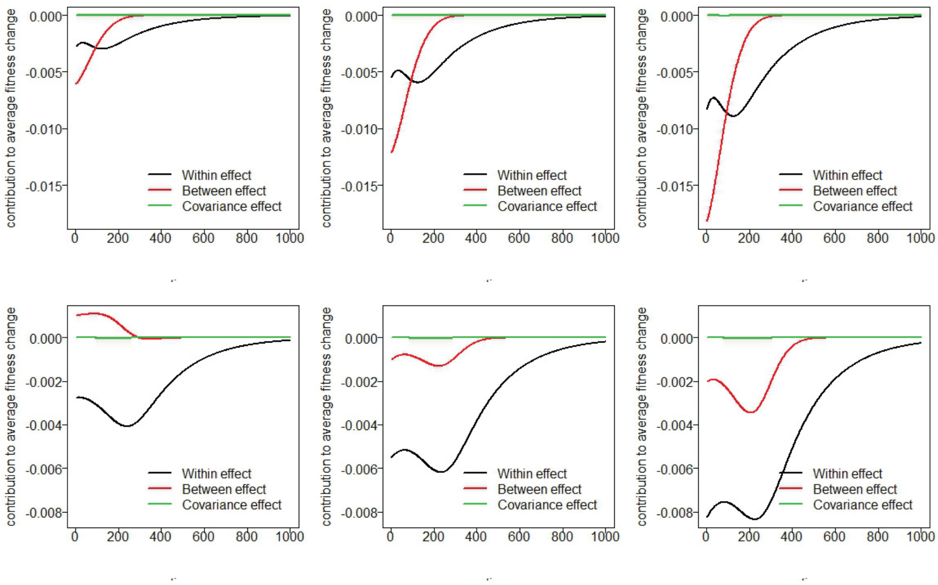

Figure 5.8: Decomposition of change in average unit cost with IRS

Note: The upper panel corresponds to ordered matching, while the lower — to random matching. From the left to the right the markets (layers) 1, 2 and 3 are shown.

5.4.3 Possibility of Partner Switching

While in in the previous two exercises the value chains were assumed to be fixed due to prohibitively high switching cost, one could relax that assumption.[8] Switching costs may involve simply a fixed cost SC, and those firms which either compensate this cost by gaining lower price of a new supplier multiplied by existing orders or gaining more orders requested by new downstream partner at the current price, will be willing to switch. We propose to model SC as percentage parameter: a firm is willing to switch a partner if it gains in fitness at least a certain percentage from the current fitness level, e.g., if the new supplier has a lower price than the old one.

To account for the fact that a firm can switch only if there is reciprocity from the other side (potential partner finds it also attractive to switch to

[8]The possibility to switch partners in a value chain is less unrealistic than it may appear at a first sight; the whole worldwide structural re–organization or production around global value chains is the most recent example that vertical relations between industries are neither completely frictionless nor totally rigid.

that firm), we introduce a simple search and acceptance algorithm ensuring reciprocity. In particular, if a firm j from a layer m_1 in a value chain x (VC^x) considers to switch its current partner jj from a layer m_2 (which can be either $m_1 + 1$ or $m_1 - 1$) and takes (randomly) firm $jk \neq jj$ from a different value chain VC^y into consideration (which in its turn has currently a partnership with firm kk from layer m_1), then those two firms, j and jk, will do the switching *iff* the fitness of the part of the value chain VC^y (firm jj from the layer m_2 is currently integrated in) j is switching to is better than the fitness of the corresponding part of VC^x, while the opposite holds true for the remaining parts of those two VCs: the fitness of the remaining part of VC^y jk is integrated to is worse in fitness than the corresponding part of the VC^x j is integrated to (see Figure 5.9).[9]

$$
\begin{array}{l}
\qquad\qquad\qquad\qquad\quad \downarrow_{switching-point}\\
VC^x = \begin{pmatrix} \overbrace{c_1^x \;\; \dots \;\; c_m^j} & | & c_{m+1}^{jj} \;\; \dots \;\; c_M^{xx} \end{pmatrix}_{1\times M}\\
VC^y = \begin{pmatrix} c_1^y \;\; \dots \;\; c_m^{kk} & | & \underbrace{c_{m+1}^{jk} \;\; \dots \;\; c_M^{yy}} \end{pmatrix}_{1\times M}
\end{array}
$$

Figure 5.9: Comparison of fitnesses for switching

Necessarily, the parameter of switching cost $SC \in [0, 1]$ becomes a key parameter, allowing situations from 'fast and easy' switching for the two firms as if no sunk costs of partnership formation exist (close to frictionless markets on upstream layers) to no switching (and respectively, no competition) at all. In what follows, we refer to a simplified case ($M = 3$ and $N = 3$) and to a more general case ($M = 10$ and $N = 10$). Figures are given for the simplified case, while the more general case is presented in the Appendix.

As in the ordered switching scenario fittest firms in the respective layers are matched together, there is basically no room left for switching. In contrast, in case of random value chain matching, firms occasionally switch (no mat-

[9] We also considered a simpler option of switching a partner when the randomly drawn candidate has a better fitness than our current partner, i.e. $c^{jj}_{m_2} - c^{jk}_{m_2} > SC \times c^{jj}_{m_2}$ and $c^{kk}_{m_1} - c^{j}_{m_1} > SC \times c^{kk}_{m_1}$. But given that this rule ignores the fitness of other partners integrated in VCs, such a rule is an oversimplification of reality and results in a much larger number of partner switches. The overall result (in terms of market reallocation and fitness improvement) is, however, consistent with our preferred acceptance algorithm.

ter whether innovative activity is present and if yes, in which scenario of scale returns). The moment of switching can be captured by the 'zig–zag' evolution (abrupt shifts) of the total unit costs of the VCs (mid–charts in all four panels of Figure 5.10) and the corresponding adjustments in the evolution of VC market shares (leftmost charts of the same figure).[10]

As a result, in early periods of simulation (which can be interpreted, for example, as early stage of an industry life–cycle) one observes a period of volatility in the market share constellation (for a better visualization consider a more complex scenario with $M = 10$ and $N = 10$, Figure 5.16 in Appendix). Except for the scenario with DRS, a dominating VC is identified relatively quickly, driving other VCs outside the market and killing any volatility in market shares dynamics. The observation on the DRS scenario is not surprising, as by design DRS is meant to preserve competition between actors for a longer period of time.What is more interesting is that the market share volatility in early periods is more universal and not so sensitive to scale returns, contrasting to the earlier argument made by Mazzucato (1998) that high volatility in the early period of life–cycle is to be found only for DRS.

Proposition 3. *Considering random matching scenario of firms vertically integrated in VCs and allowing them to switch, one observes a high volatility in market share dynamics at the beginning of the simulation (corresponding to early period of industry life–cycle) irrespective of the specific return to scale mode.*

[10] Since for ordered matching the possibility of switching is never exploited, we do not include the related charts.

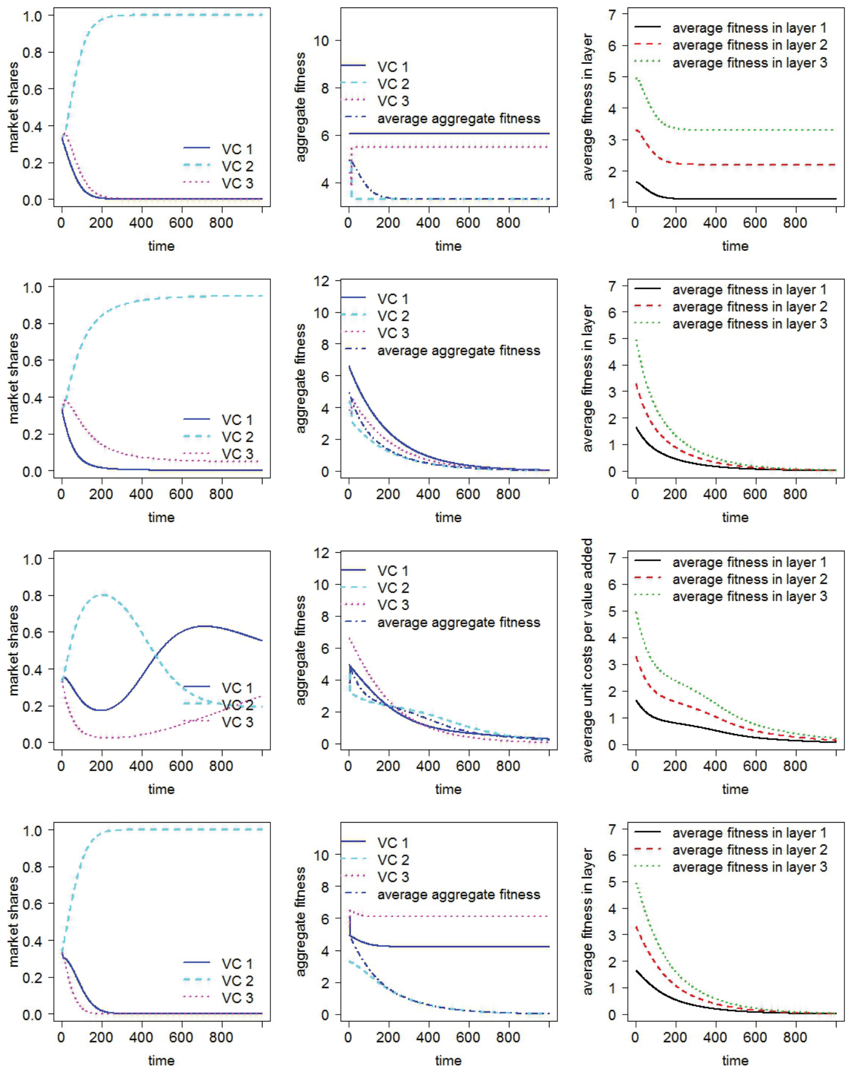

Figure 5.10: Dynamics with random matching, different innovation scenarios and switching

Note: The upper panel corresponds to no innovation, the next to innovation with CRS, the third from the top to innovation with DRS, and the bottom one to innovation with IRS. $M = 3$, $N = 3$, $SC = 10\%$ and $\gamma = 0.005$.

In Figure 5.11 one can find the corresponding decompositions into the between, within and covariance effects for the four scenarios with switching. Given that the firms in the VCs are connected via constant quantity relations (the firm in the last market competes for an output quantity (market share) and the upstream firms serve as suppliers of intermediary products for this final quantity), a switch of a VC partner implies a large change in the output quantity producing an instantaneous shock, which takes place synchronously on all M layers, but with different magnitudes.[11]

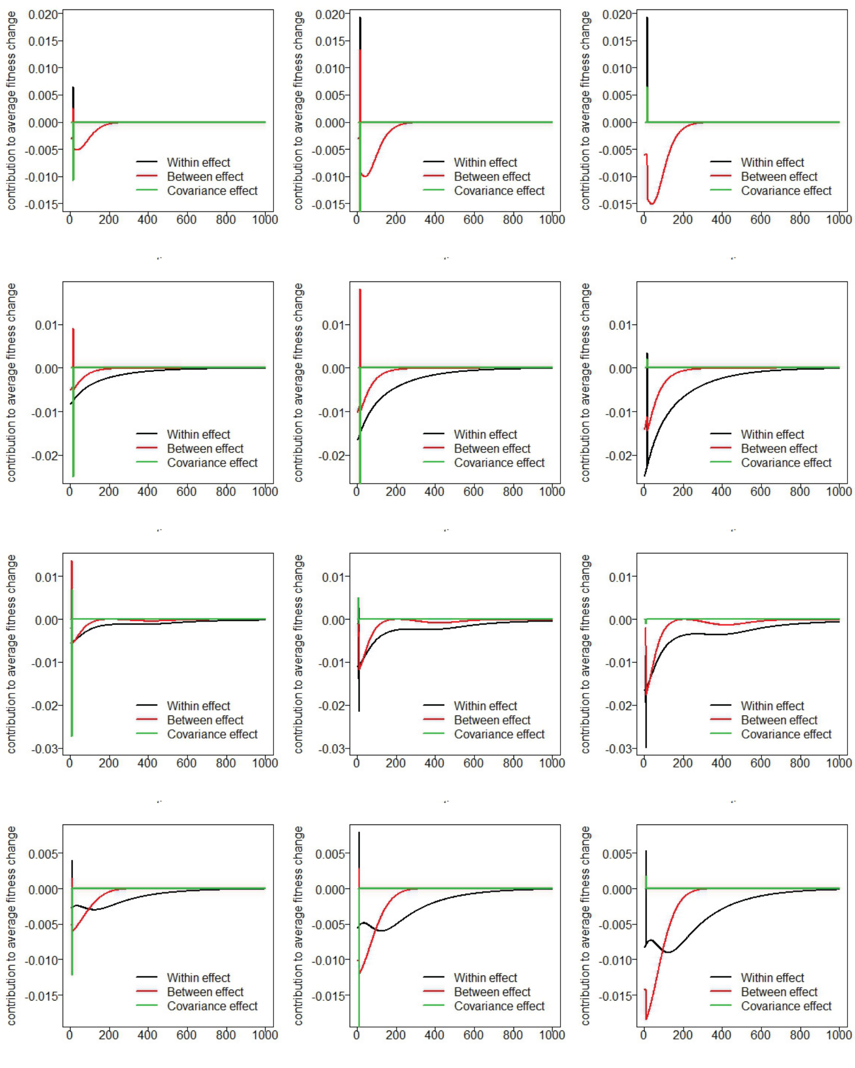

Figure 5.11: Decomposition of change in average unit cost for different innovation scenarios and switching

Note: The upper panel corresponds to no innovation, the next to innovation with CRS, the third from the top to innovation with DRS, and the bottom one to innovation with IRS.

Thus, firms in the up– or downstream part of VC having switched to a stronger group of partners experience a sudden increase in their market

[11]This is due to the different deviation of each VC member's layer–specific cost level from the market–weighted mean layer–specific cost level, see (5.11).

share. Given that by construction switching requires reciprocity and more fit firms tend to build stronger VCs, most of the time firms gaining additional market shares have a cost below their market average, which results in negative shocks. As a result, we observe those negative shocks in the between effects, depicted by the red line in Figure 5.11. Those shocks clearly correspond to the moments when switching takes place and are concentrated in the early periods of simulation (see also Figure 5.17 in the Appendix).

The main reason why the switches (and the corresponding shocks in the between effect) tend to take place so early is that the cost differences in the early phases are stronger (this holds true for all scenarios with innovation) so that the term indicating the deviation from the cost average $\left(C_m^{i,t-1} - \bar{C}_m^{i,t-1}\right)$ is also stronger. The other reason distinguishing somewhat the simplified and the the more general cases is that the total number of possible 'reconfigurations' of the value chains, though being different becomes quickly exploited within the first few hundred periods of the simulation run.

5.4.4 Summary on the Average Unit Cost Decomposition

To better summarize the differences between scenarios considered in terms of the average layer–specific unit cost decomposition, consider Table 5.1, where the three effects are averaged over all M (here $M = 10$ and $N = 10$ are taken as default) layers and all T (as before, equal to 1000) periods for 1000 restarts. Comparing the left and right hand side of the table one immediately notices that the between effect in the random matching is consistently less strong than in ordered VC matching, which is due to the fact that only in some markets the replicator dynamics works in the 'right' way, while in others — firms performing worse than market average but integrated in stronger VCs improve their market position. Notably, in the random matching scenario the within effect clearly dominates the between effect in all but no innovation scenario.[12] Such result generally supports our idea

[12]Within effect directed on firm specific fitness here is certainly zero. However, since firm's total fitness includes costs of input, the within effect can deviate from zero due to switching. Note that comparing ordered and random matching in case of no innovation proves the between effects and the overall improvement to be always higher for the former

that the clear–cut expectated results of market selection are made more ambiguous by the learning and innovation processes.[13]

Looking at the results with the possibility of switching partners within a value chain (second and third panels in Table 5.1), we observe the following outcomes for the random matching case:

1. in the scenario with no innovation, the possibility of switching hastens fitness improvement. This result is logical as one can recombine the structures of a VC in a more efficient way than the original random structure achieving a higher efficiency (compare lower panel of Figure 5.2 with the upper one in Figure 5.10). Increasing the cost of switching SC to 50% (making it less frequent so that it takes place when both sides have very large benefits from changing their upstream/downstream partners), limits the possibility of VC 'optimization' and mitigates its effect on fitness improvement;
2. in the scenarios with innovation (CRS, DRS and IRS), no clear pattern is found, apart for the role of the between effect that increases for DRS when $SC = 10\%$. The within effect increases the more costly is the switch (as it becomes more costly to improve VC competitiveness by partner switching and one has to rely more on internal improvements (R&D)).

Summarizing the results above, we can outline a fourth result of our simulation exercise:

Proposition 4. *For randomly matched value chains, the possibility of switching boosts the change in aggregate fitness in the case of no innovation. The possibility of partner switching and the cost of partner switching affect in different ways the working of the replicator dynamics, with the clearer positive effect on selection to be found in case of DRS and low switching costs.*

case, which is consistent with our prediction.

[13]Another interesting observation from Table 5.1 is the fact that for DRS both for ordered and random VC matching the difference of the between and the within effects is largest, which is due to the fact that in this particular returns to scale scenario change in costs slows down due to increasing market shares and, as a result, one observes more dynamics in $\Delta s_m^{i,t}\left(C_m^{i,t-1} - \bar{C}_m^{i,t-1}\right)$ than in $s_m^{i,t-1}\Delta C_m^{i,t}$. In other words, in case of DRS firms reach a smaller progress in cost reduction but exhibit a larger market share reallocation dynamics, which reflects in larger values of the between effect.

Table 5.1: Results for the average unit cost decomposition over different scenarios

		Ordered VC matching			Random VC matching		
		Between Effect	Within Effect	Covariance	Between Effect	Within Effect	Covariance
Without Switching	No innovation	−0.0136	0	0	−0.0045	0	0
		(0.1174)	(0)	(0)	(0.0251)	(0)	(0)
	CRS	−0.0130	−0.0067	0.0001	−0.0038	−0.0157	0.0000
		(0.1143)	(0.0122)	(0.0006)	(0.0226)	(0.0246)	(0.0001)
	DRS	−0.0155	−0.0040	0.0000	−0.0051	−0.0143	0.0000
		(0.1142)	(0.0084)	(0.0006)	(0.0225)	(0.0197)	(0.0002)
	IRS	−0.0137	−0.0059	−0.0000	−0.0051	−0.0143	−0.0000
		(0.1173)	(0.0081)	(0.0000)	(0.0254)	(0.0186)	(0.0001)
Switching, $SC = 10\%$	No innovation	−0.0136	0	0	−0.0019	0.0089	−0.0167
		(0.1174)	(0)	(0)	(0.2726)	(0.3088)	(0.5540)
	CRS	−0.0130	−0.0067	0.0001	−0.0035	−0.0106	−0.0055
		(0.1143)	(0.0122)	(0.0006)	(0.1031)	(0.1140)	(0.2033)
	DRS	−0.0155	−0.0040	0.0000	−0.0079	−0.0100	−0.0014
		(0.1142)	(0.0084)	(0.0006)	(0.1072)	(0.1257)	(0.2181)
	IRS	−0.0137	−0.0059	−0.0000	−0.0039	−0.0080	−0.0077
		(0.1173)	(0.0081)	(0.0000)	(0.1843)	(0.1983)	(0.3616)
Switching, $SC = 50\%$	No innovation	−0.0136	0	0	−0.0043	0.0004	−0.0008
		(0.1174)	(0)	(0)	(0.0781)	(0.0890)	(0.1575)
	CRS	−0.0130	−0.0067	0.0001	−0.0038	−0.0156	−0.0002
		(0.1143)	(0.0122)	(0.0006)	(0.0325)	(0.0377)	(0.0516)
	DRS	−0.0155	−0.0040	0.0001	−0.0051	−0.0142	−0.0000
		(0.1142)	(0.0084)	(0.0006)	(0.0269)	(0.0285)	(0.0366)
	IRS	−0.0137	−0.0059	−0.0000	−0.0048	−0.0135	−0.0012
		(0.1173)	(0.0081)	(0.0001)	(0.0920)	(0.0999)	(0.1813)

Note: Results are averaged over 1000 restarts for all vertically integrated layers and time periods. Standard deviations are reported in parentheses.

It is useful at this point to analyze how the between, within and covariance effects vary *between* the layers of a value chain. We investigate how the disproportion in distribution of the between, within and covariance effects between layers changes with respect to the number of layers considered, experimenting with the cases featuring three, five, seven and nine layers (keeping the number of layers odd to simplify selection of the 'mid' layers, $\frac{M-1}{2}+1$ following the notation used so far). Results of the experiment are presented in Figure 5.12. In general, the pattern that emerges is one in which — both in ordered and random matching — the between effect is stronger for layers being closer to the final market. In fact, all three type of effects are concentrated on the bottom (M) layer, while with the increasing number of layers the disproportion in the distribution of the effects increases consistently. This is particularly pronounced for the CRS and DRS cases, where the within effects are about five times bigger (in case of nine layers) in the bottom layer compared to the upper layer. The fact that different layers are heterogeneously affected by selection dynamics provides a matter of discussion for policy and in particular for competition policy. Markets that are linked in value chains require different sets of policy measures according to the strength of competition and reallocation. At the same time, knowing the heterogeneous magnitudes of selection dynamics in different layers of the value chains may affect firms' strategic decisions regarding the establishments of specific value chain linkages.

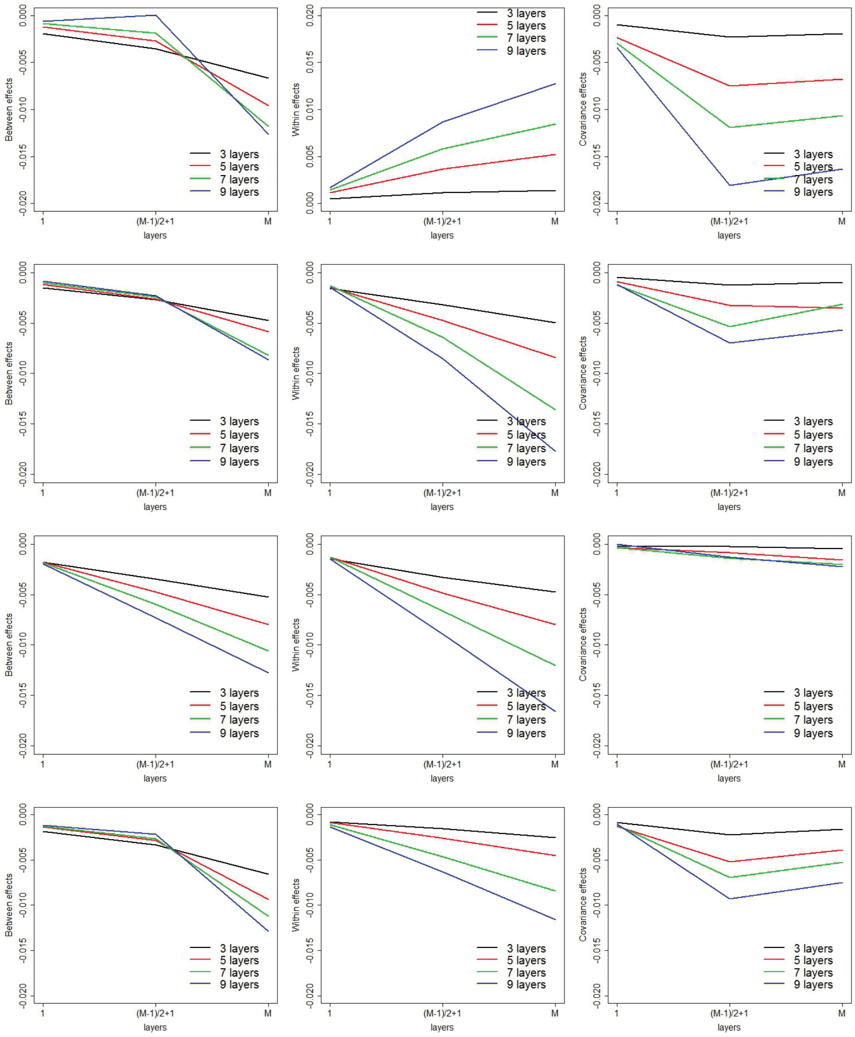

Figure 5.12: Dynamics in the decomposition into between and within effects for different number of layers

Note: The upper panel corresponds to no innovation, the next to innovation with CRS, the third from the top to innovation with DRS, and the bottom one to innovation with IRS. $M = 10$, $N = 10$ and $SC = 10\%$.

This experiment on the distribution of the within, between and covariance effects with respect to the number and position of the layers of the VC allows us to derive a fifth result:

Proposition 5. *For all the types of value chains, selections affects different layers (markets) in different ways. More specifically, the replicator dynamics intensifies its effect the closer the layer is to the final market. The* *heterogeneous distribution of selection effects across value chain's layers has implications for competition policy, that may discriminate firms according to their position in the value chains, and for firms' strategic decision on value chain positioning.*

5.5 Conclusion

In this Chapter we generalize the replicator dynamics model to the case of firms vertically related in value chains. For that we conduct a series of exercises starting from the most simplest one without innovation to three innovation cases and increasing the complexity stepwise. Doing this, we contrast two scenarios with firms being matched according to the performance rank of its members (ordered matching scenario) and those being matched completely randomly. In addition, we introduce a simple rule of partner switching ensuring reciprocity from both sides. Then, using some analytical but mainly computational tools, we show how the two scenarios differ.

A result of this exercises is the series of propositions 1-5. First of all, we demonstrate that firms being related into VC structure and depending in their output capacity on their downstream partners do not necessarily increase their market share even though being most efficient that is, having higher (lower) fitness (total unit cost)) on their respective layers. This is due to limited competition on upstream markets (firms being locked–in into VCs) and aggregate fitness of a VC being crucial for the success on the final consumer market. Relatedly, the very existence of VC relations may induce violations of the replicator dynamics generating what we called regressive developments of market selection; in these situations the average fitness may decrease rather than increase over time.

Furthermore, we show that for firms in the random VC matching scenario with the possibility to switch partners produces at the beginning a period of high market share volatility dynamics in any innovation and returns to scale setting, which provides a novel and simpler explanation to the evidence discussed by Mazzucato (1998).

Next, our two last results indicate that the possibility of partner switching, coupled with different 'regimes' of switching costs, hastens the change in aggregate fitness (for randomly matched value chains) and affects with various intensities selection dynamics. Moreover, market selection affects with different magnitudes different value chains layers, with the strongest effect to be found at the final end of the value chain. The latter results may be taken into consideration to derive policy implications. Although policy makers have generally limited influence on firms' strategic decisions with regard to partner selection, certain measures such as increasing market transparency or financial support for firms at the early period of alliance formation may come in question to facilitate the 'survival of the fittest' principle and to support productivity improvement on a given market.

Our results call both for more differentiated analyses of the replicator dynamics on different stages of value creation[14] and possibly different competition policy measures applied for different markets. In general, the idea that market selection may 'bite' more in certain layers of a value chain opens two broad sets of research questions to be analysed; first, how policy interventions targeting innovation and competition should focus more on upstream and downstream bottlenecks rather than just looking at a single layer rate of innovation and production. Second, how the current reconfiguration of production into global value chains (Timmer et al., 2014) has been affected by (and can affect) the Schumpeterian competition for the market.

For further research we plan to explore at least two main trajectories: First, to deepen our understanding and identification of the VC structures under which the replicator dynamics is violated and regressive developments take place; Second, to generalize the exercise allowing firms to partner more than one firm from the same layer at the same time. This should allow to address network properties of production chains. Furthermore, one can draw better intuition on differences between layers in terms of their alliance formation power and firm survival.

As a conclusion, by introducing value chains into the mechanism of market

[14]Thus, while it may be easier to find evidence for the replicator model on the downstream market, such as stage of assembling and selling compact cars, it is more challenging for producers of intermediate parts, and one has to take this into account.

selection, our contribution sheds a light on the multidimentional nature of the replicator dynamics model; instead of confining it among the theoretically elegant but empirically irrelevant economic tools, we hope this will induce new attempts to enrich its framework and understand its validity and explanatory power.

5.6 Appendix

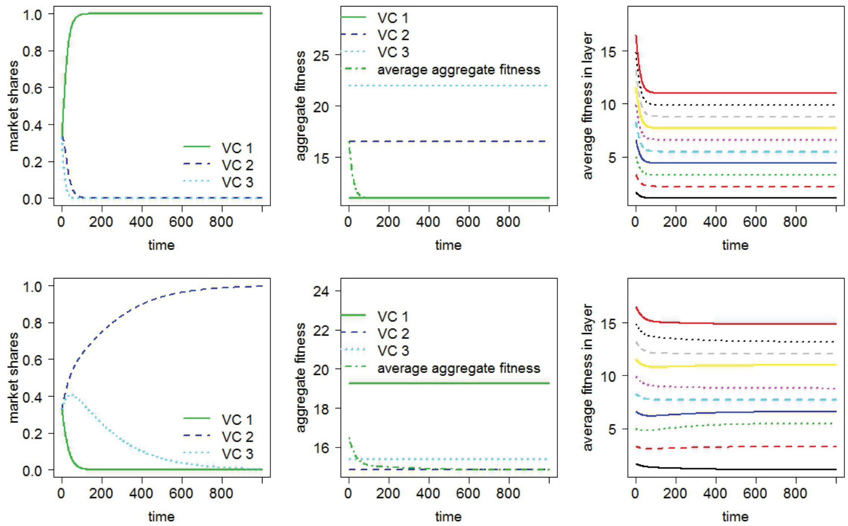

Figure 5.13: Dynamics with ordered and random matching with ten layers

Note: The upper panel corresponds to ordered matching, while the lower to random matching. $M = 10$ and $N = 3$.

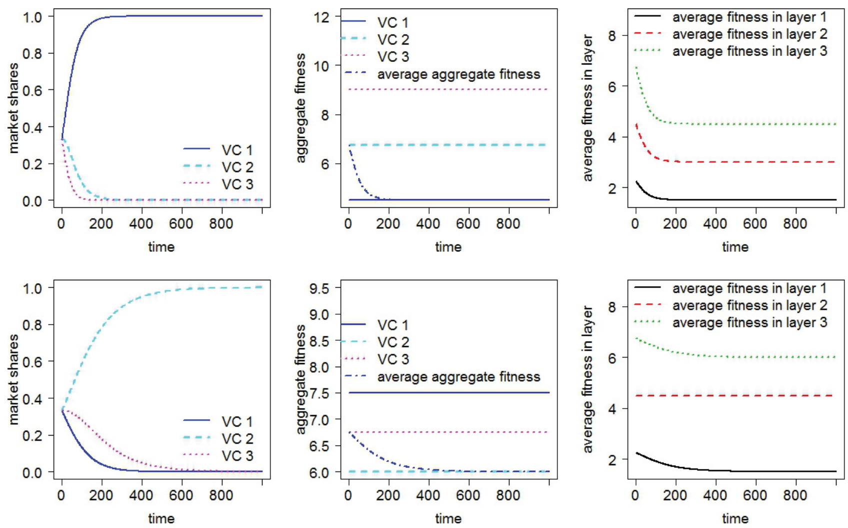

Figure 5.14: Dynamics with ordered and random matching with alternative profit margin

Note: The upper panel corresponds to ordered matching, while the lower to random matching. $M = 3$, $N = 3$ and $\phi = 0.5$.

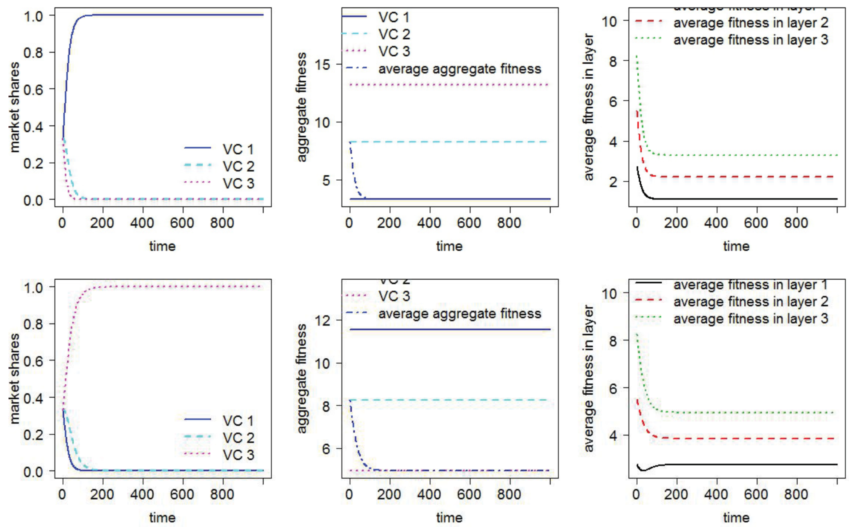

Figure 5.15: Dynamics with ordered and random matching with larger variance in fitness

Note: While in the default case, as it was mentioned earlier, firms' productivity has been drawn in a way that each firm surpasses the next one by 0.5 (which was leading to $(\sigma_c^m)^2 \approx 0.167$), here we increase the step to 1 and, respectively, the$(\sigma_c^m)^2$ to ≈ 0.67.
The upper panel corresponds to ordered matching, while the lower to random matching. $M = 3$ and $N = 3$.

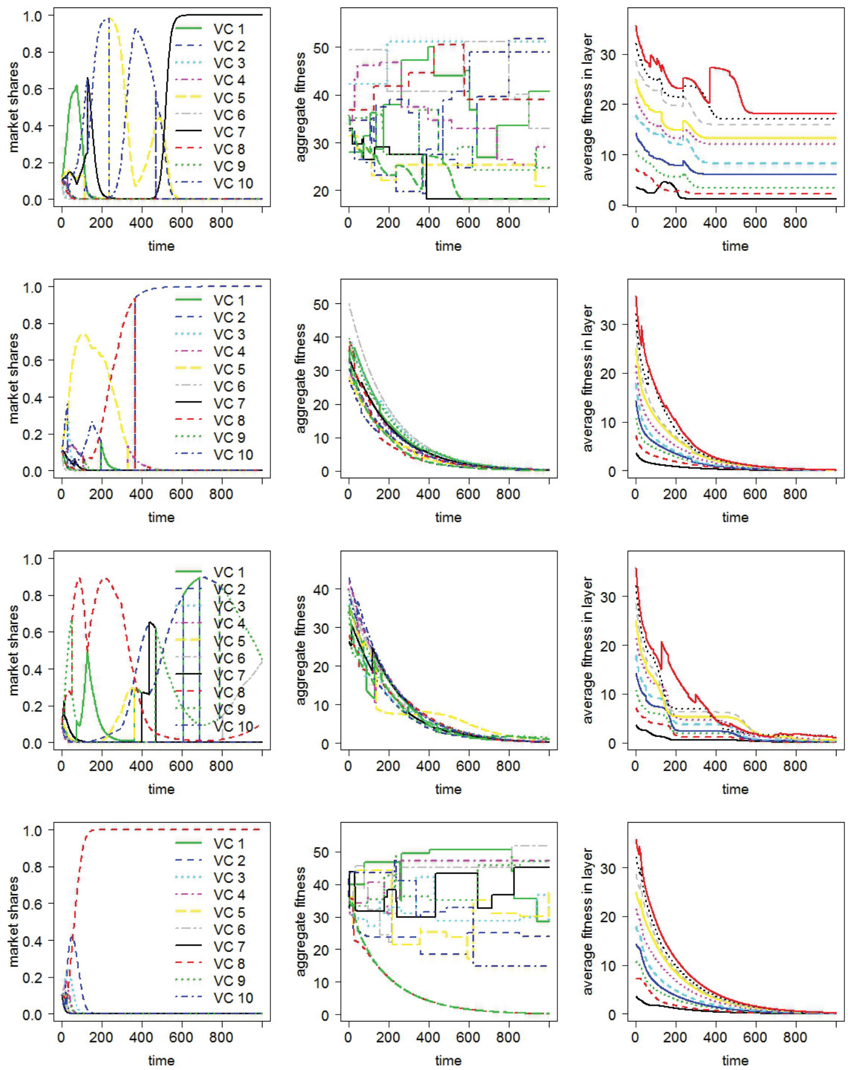

Figure 5.16: Dynamics with random matching and switching for different innovation scenarios

Note: The upper panel corresponds to no innovation, the next to innovation with CRS, the third from the top to innovation with DRS, and the bottom one– to innovation with IRS. $M = 10$, $N = 10$ and $SC = 10\%$.

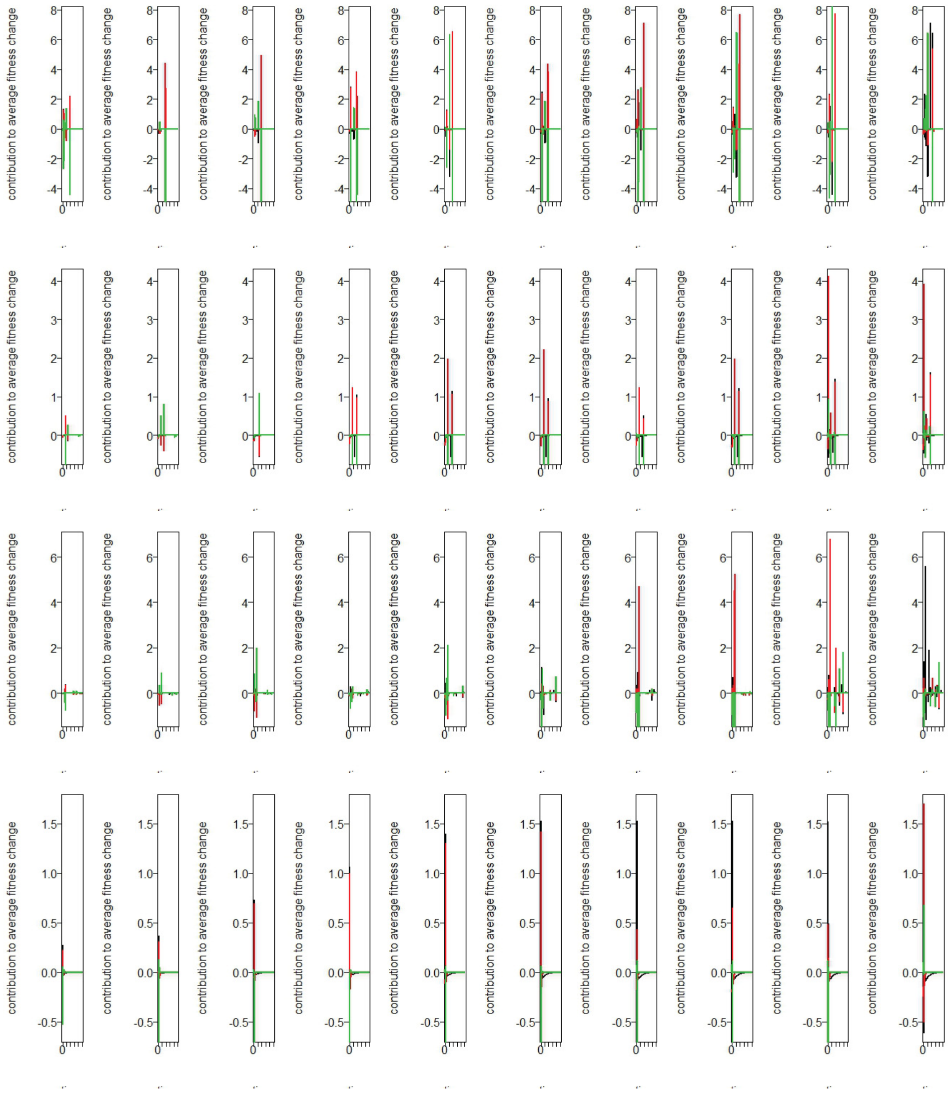

Figure 5.17: Decomposition of change in average unit cost for different innovation scenarios

Note: The upper panel corresponds to no innovation, the next to innovation with CRS, the third from the top to innovation with DRS, and the bottom one- to innovation with IRS. $M = 10$, $N = 10$ and $SC = 10\%$.

Chapter 6

Short– and Long–run Effects of External Interventions on Trust

6.1 Introduction

In 1998, Stanford University licenses the *PageRank* patent to one of its newly established spinoff companies. This investment initiates the growth of one of the worlds' largest high tech company *Google* that soon revolutionizes the IT market and changes the whole world economy. Besides public economic impact, this investment brings private financial benefits to Stanford that in large extent include voluntary financing of research scholarships and common projects.[1]

The success of Google explains why governments often intervene aiming to foster the academic spinoff creation and knowledge commercialization. Typically, such intervention takes the form of subsidy–policy that comprises two phases: First, a university receives a subsidy if it invests in the spinoff; Sec-

[1] For instance, in 2008, Google paid approximately $1,881,400 to Stanford University out of which only $426,950 payments related to the license of patents. The largest part of the payments — about $1,246,000 — was donations for scholarships and other philanthropic endeavors (Wikinvest.com, 2009).

ondly, the successful spinoff gains additional finances from the government.[2]

Alternative forms of policy such as targeting are rarely considered, though they may not involve subsidy spending. Moreover, since the policy makers are often focused on immediate consequences of the interventions, the long term, post–intervention potential costs are not taken into account. We attempt to fill this gap using controlled laboratory experiment that allows to make a direct comparison of different policies' efficiency in the short– and in the long–run.

In this experiment we analyze the effects of external intervention such as subsidy and targeting on the investment decision during the intervention and after. We employ a multi–period version of the trust (investment) game (Berg et al., 1995) introducing either the monetary incentives for contribution or providing a suggestion about the level of investment. The experiment consists of three blocks with policy intervention in the second one that let us to consider immediate as well as post–intervention effects.

The study offers three main original contributions: First, we analyze the effect of non–monetary intervention in form of suggestion on trustful behavior; Second, we compare the effect of non–monetary policy to monetary ones; Third, we provide an analysis of the long–run effects of external interventions on trust.

More specifically, we aim to answer the next four questions: i) Do non–monetary intervention such as suggestion increase investment activity during and after they are introduced? ii) Is subsidy policy an efficient mean to foster investment activity in the short–run? iii) Is a low level of investment required to receive a subsidy detrimental for an investment? iv) Does the subsidy policy have a negative impact on investment level after the policy termination?

We find that non–monetary policy in form of suggestion increase investment activity during the intervention and we do not find any detrimental effects afterwards. Subsidy policy, however, does not significantly affect the level

[2] See, for example, programs such as 'Small Business Technology Transfer' (SBTT) in the United States and '*Existenzgründungen aus der Wissenschaft*' (EXIST) in Germany.

of trust in the short– or in the long–run. We associate the ineffectiveness of subsidy policy with two regularities: Subjects show low propensity to follow this policy and if subjects follow it, they send mostly the lowest amount required to get the subsidy.

We also find indirect evidence that the monetary policy is ineffective not because of the presence of the subsidy itself but rather from the fact that monetary reward is conditioned on a certain behavior: Subjects that unconditionally receive subsidies do not show a significantly different level of trustworthiness. We conclude that targeting policy should be considered as an effective tool to foster investment activity.

The rest of the Chapter proceeds as follows: Section 6.2 provides a short review of the relevant literature. Section 6.3 describes the theoretical framework and the hypotheses. Section 6.4 presents the experimental design. Section 6.5 provides the results of the experiment. Section 6.6 then discusses the findings, followed by some final remarks.

6.2 Related Literature

The Chapter builds on three different strands of literature.

First, it relates to studies on interaction between intrinsic and extrinsic motivation. From the early research of Titmuss (1970) on blood donations to the experiment of Andreoni (1993) on public good provision, the studies point out the potential detrimental effects of external interventions on intrinsic motivation. For instance, in a meta-analysis of experimental studies on external incentives and intrinsic motivation, Deci et al. (1999) indicate the presence of negative effects that are particularly relevant in case of tangible rewards.

Bowles and Polania-Reyes (2012), however, come to a different conclusion evaluating the results of experiments on the relation between incentives and social preferences. They note that the effect of the incentives depends on the pre-existing social framework and can be both negative and positive. Gneezy et al. (2011) extend this discussion urging to consider both the potential long term costs and benefits of external interventions.

The second strand of literature looks at the role that trust plays in investment decisions. Trust is involved in almost every economic transaction (Arrow, 1972) and, indeed, the empirical evidence suggests that the trust is crucial for venture capital investments (Bottazzi et al., 2011), mutual investment decisions (Felli et al., 2010) and has a positive association with the level of investment across countries (Knack and Keefer, 1997).

The trust (investment) game that we employ in the experiment mirrors the investment situation with imperfect contracts. The behavior in this game varies across countries with different economic characteristics (Johnson and Mislin, 2011). Moreover, the trustful behavior in this game correlates with the differences in investment propensity between countries — for instance, Germany and France (Willinger et al., 2003) or Gulf region and Western countries (Bohnet et al., 2010) — that make it possible to better understand the variation in the investment rates across nations.

Thirdly, this Chapter is closely related to the studies of the interaction between external incentives and trustful behavior. Fehr and List (2004) find that the threat to punish increases trustworthiness, but the punishment crowds out trustworthy behavior. Furthermore, Bohnet et al. (2001) find that the threat of potential contract enforcement crowds in trustworthiness, although this effect depends on the level of enforcement.

Studying the effect of various incentives on trustful behavior Charness et al. (2008) allow a third–party not only to punish but to reward as well. The experimental results corroborate the hypothesis that the threat of punishment increases trust and trustworthiness. However, the effect of reward on trust is rather ambiguous.

Gachter et al. (2011) further extend the research on the effect of punishment and rewards on trustworthiness. Using a multi–phase gift–exchange game they find that trustworthiness (exerted effort) increases both in the presence of a fine or a bonus. Nevertheless, the effect of the bonus is much smaller than the effect of the fine due to the crowding out: Under the bonus condition subjects tend to choose an effort not higher than a best–reply level.

As concerns the effect of non–monetary incentives on trust, Bracht and Feltovich (2009) show that the information about the previous actions of others can enhance cooperation.[3] Moreover, Berg et al. (1995) provide evidence that even an aggregated information about previous behavior — information about the average amount sent by other subjects — can strengthen trustful relations. Similarly, Thöni and Gachter (2012) show that peer–effects have a significant influence on the trust level and suggest conformism as an explanation of this phenomenon.

6.3 Theory and Implications

6.3.1 The Game

We use a version of the trust (investment) game. In the original trust game (Berg et al., 1995), two players interact with each other: player 1 (the trustor) decides which amount of his initial endowment E to send (to give) to player 2 (the trustee). The amount sent s is multiplied by a certain factor m and player 2 receives the multiplied sum. Player 2, in turn, chooses how much to return R of the amount received. See Figure 6.1 for the structure of the game and a description of the payoffs π of players 1 and 2.

In our version of the investment game, an external intervention is introduced. This intervention is devised alternatively as either a subsidy or a suggestion. The subsidy Z is obtained by both players if the contribution of player 1 is greater than or equal to a certain threshold T (figure 6.2 describes this version of the game). In the case of suggestion, no subsidy is available but it is suggested to send not less than a threshold level.

The game is played for several periods and consists of three blocks. Blocks 1 and 3 consist of repetitions of the standard trust game, while in the block

[3] In addition, Duffy and Feltovich (2010) find that the recommendation by third–party affects subjects behavior in the two–player game of Chicken.

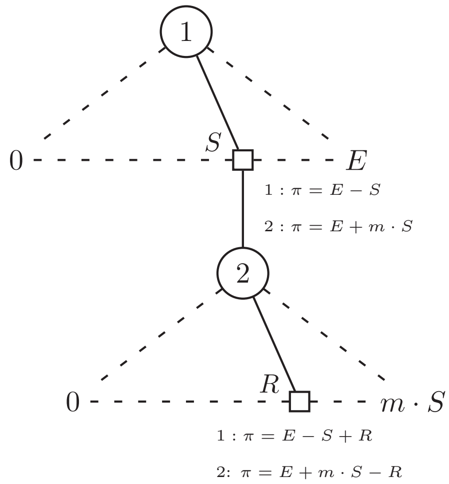

Figure 6.1: Trust (investment) game

2 the interventions are introduced.

In what follows, we outline a simple model to develop the theoretical predictions and hypotheses.

6.3.2 Trust under External Incentives

To derive the theoretical predictions, we apply backward induction solving the model from the second stage. We denote by v the value that trustor expects to receive back in the second stage of the game. This value is a function of the amount sent s. Thus, the utility function of the trustor takes the form:

$$u = E - c(s) + v(s) + o(s) + I, \tag{6.1}$$

where E is the player's endowment, c is the individual's cost of sending an amount s, o is the trustor's other–regarding preferences that depend on s, I is the effect of external incentives that can take the form of either a subsidy or a suggestion.

Let's begin the analysis with the subsidy policy. The subsidy policy is characterized by a tuple of parameters (Z, T), indicating the size of the subsidy and the threshold (minimal) amount that the player must send to

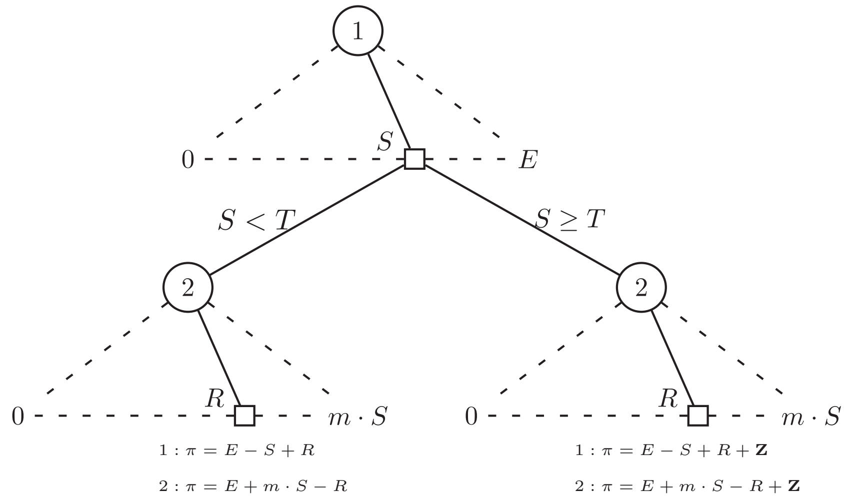

Figure 6.2: Trust (investment) game with subsidies

obtain this subsidy, respectively.

The subsidy offsets the costs of sending but can affect other-regarding preferences as well. We assume that the other-regarding preferences are affected by a measure $\lambda < 0$.[4] Thus, the utility function in the presence of a subsidy policy is

$$u = E - c(s) + v(s) + o(s) + 1_{\{s \geq T\}}[Z + \lambda o(s)], \tag{6.2}$$

where the indicator $1_{\{s \geq T\}} = 1$ if $s \geq T$ and zero otherwise.

The players maximize their utility so that the marginal costs of sending are equal to the marginal benefits (the values are expressed in discrete terms to account for the discontinuity in $s = T$):

$$\frac{\Delta c(s)}{\Delta s} = \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{\Delta 1_{\{s \geq T\}}[Z + \lambda o(s)]}{\Delta s}, \tag{6.3}$$

To analyze the effect of a subsidy policy, we compare it to the case where there are no incentives. The subsidy is contingent on the relation between threshold and amount sent. We therefore consider two states (1) when the amount to be sent without incentives s_0 is lower than the threshold and (2)

[4] We make this assumption in line with previous experimental results. See Bowles and Polania-Reyes (2012) for a discussion.

when it is higher. We then obtain the following two relations:

$$\frac{\Delta c(s^*)}{\Delta s} = \begin{cases} \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{Z}{\Delta s} + \frac{\lambda \Delta o(s)}{\Delta s} & \text{if } s_0 < T \\ \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{\lambda \Delta o(s)}{\Delta s} & \text{if } s_0 \geq T \end{cases} \tag{6.4}$$

One can easily see that it is beneficial to send more whenever the amount to be sent without incentives s_0 is lower than the threshold T and the direct effect of the subsidy $\frac{Z}{\Delta s}$ is larger than the crowding out effect of the subsidy $\frac{\lambda \Delta o(s)}{\Delta s}$. However, if $s_0 < T$, there is no direct subsidy effect (the subsidy is independent from additional sending, $\frac{Z}{\Delta s} = 0$), whereas the negative effect of the subsidy on other–regarding preferences is still present, $\frac{\lambda \Delta o(s)}{\Delta s} < 0$. We are therefore able to formulate the following two hypotheses:

Hypothesis 1. *The amount sent is higher under external monetary incentives than without them if (1) the threshold level is higher than the amount sent in case without the incentives $s_0 < T$ and (2) the direct effect of the subsidy is larger than the crowding out effect $\frac{Z}{\Delta s} + \frac{\lambda \Delta o(s)}{\Delta s} > 0$.*

Hypothesis 2. *The amount sent is lower under external monetary incentives than without them if the threshold level is higher than the amount sent in case without the incentives $s_0 < T$.*

Concerning the targeting policy (suggestion), this policy is also characterized by a threshold level T (the suggested minimal level to be sent). The policy does not use subsidy but players can get an utility complying with authority (Karakostas and Zizzo, 2012).[5] We denote this utility by A (that is independent from s). Thus, the senders' utility is

$$u = E - c(s) + v(s) + o(s) + 1_{\{s \geq T\}}(A), \tag{6.5}$$

Analyzing the players' utility function in the case of targeting policy in the same way as in 6.3 and 6.4, we obtain the next relations:

[5] In Karakostas and Zizzo (2012), the information communicated by a third-party affects the behavior of subjects. They attribute this effect to compliance to authority. We suppose that the suggestion have a similar effect.

$$\frac{\Delta c(s^*)}{\Delta s} = \begin{cases} \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{A}{\Delta s} & \text{if } s_0 < T \\ \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} & \text{if } s_0 \geq T \end{cases} \tag{6.6}$$

If the amount sent in case without the incentives is lower than the threshold $s_0 < T$ the players benefit by complying with authority. Therefore, they can sacrifice part of their endowment to follow the suggestion. Nevertheless, they do not benefit when $s_0 > T$ since the utility is independent from the amount sent.

Hypothesis 3. *The amount sent is higher under external non–monetary incentives than without them if the threshold level is higher than the amount sent in case without the incentives $s_0 < T$.*

Considering the long–run (post–intervention) effect of incentives, we assume that preferences are endogenous (Bowles, 1998), meaning that the preferences learned under certain circumstances stay present afterwards. Given this, we can derive from 6.4 the following relations for the period after the subsidy policy:

$$\frac{\Delta c(s^*)}{\Delta s} = \begin{cases} \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{\lambda \Delta o(s)}{\Delta s} & \text{if } s_0 < T \\ \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{\lambda \Delta o(s)}{\Delta s} & \text{if } s_0 \geq T \end{cases} \tag{6.7}$$

There is no direct effect of the subsidy Z since the subsidy policy is absent now. However, other-regarding preferences are still negatively affected $\frac{\lambda \Delta o(s)}{\Delta s} < 0$. Thus, we formulate:

Hypothesis 4. *The amount sent is lower after experiencing external monetary incentives than without them.*

In a similar vein, we derive from 6.5 the next relations for the period after the targeting policy:

$$\frac{\Delta c(s^*)}{\Delta s} = \begin{cases} \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} + \frac{A}{\Delta s} & \text{if } s_0 < T \\ \frac{\Delta v(s)}{\Delta s} + \frac{\Delta o(s)}{\Delta s} & \text{if } s_0 \geq T \end{cases} \tag{6.8}$$

When the threshold level is higher than the amount sent in case without the incentives $s_0 < T$, the players send more after the targeting policy since they continue to gain utility complying to the authority $\frac{A}{\Delta s} > 0$.

Hypothesis 5. *The amount sent is higher after experiencing external non-monetary incentives than without them if the threshold level is higher than the amount sent in case without the incentives $s_0 < T$.*

6.3.3 Trustworthiness under External Incentives

We represent the utility function of the trustee in the following way:

$$u = 1 - c(r) + o(r) + I, \tag{6.9}$$

where $c(r)$ is the trustee's cost of returning the ratio $r = \frac{R}{m \cdot s}$, o is the other regarding preferences that changes with r[6], I is the effect of external intervention (subsidy or suggestion).

We assume that trustees maximize their utility. Since external intervention depends on the behavior of trustor but not on trustee's choice we obtain the following relation:

$$\frac{\partial c(r^*)}{\partial r} = \frac{\partial o(r)}{\partial r}, \tag{6.10}$$

We know from previous studies (Johnson and Mislin, 2011) that $\frac{\partial c(r^*)}{\partial r \partial s} = \frac{\partial o(r)}{\partial r \partial s} > 0$. Therefore, we can formulate the following hypothesis:

Hypothesis 6. *The trustworthiness rate r is not different during and after the external intervention as compared to the case without it when conditioned on the amount sent by the trustor s.*

[6]We assume that o is independent from Z since (1) subsidy is provided by a third-party and (2) both players receive it.

6.4 Experimental Design

The experiment was conducted at the laboratory of the Max Planck Institute of Economics in Jena (Germany) in April 2013. Seven sessions were run, each of them lasting about 60 minutes and employing 32 experimental subjects. Experimental subjects were recruited using the ORSEE system (Greiner, 2004), and the experiment was programmed and implemented with the help of the software z–Tree (Fischbacher, 2007).

In the experiment, subjects play various versions of the trust game for 30 periods. In each period, they have an endowment of 100 points, $E = 100$, and the sum that they send is tripled, $m = 3$. The experiment is subdivided into three blocks of 10 periods each. The first and the third blocks are the same for all subjects — they face the standard trust game. However, in the second block, subjects play different versions of the trust game depending on the treatment to which they are randomly assigned: SUBLOW, SUBHIGH, SUGGEST, CONTROL.

In the second block of the SUBLOW treatment, subjects can gain a subsidy of 20 points, $Z = 20$, if the amount sent by the trustor exceeds a (low) threshold of 30, $T = 30$. See the game flow for the SUBLOW treatment in Figure 6.3.

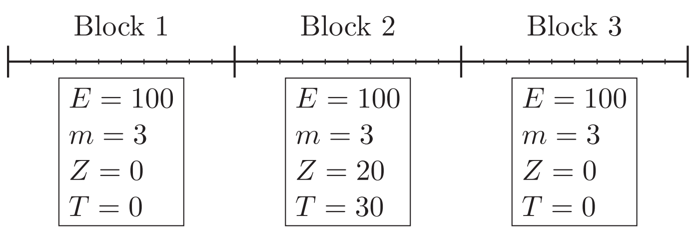

Figure 6.3: SUBLOW treatment parameters

The SUBHIGH treatment differs from the SUBLOW treatment only in the threshold level: To gain the subsidy the trustor needs to send not less then 70, $T = 70$. See Figure 6.4.

Block 1	Block 2	Block 3
$E = 100$	$E = 100$	$E = 100$
$m = 3$	$m = 3$	$m = 3$
$Z = 0$	$Z = 20$	$Z = 0$
$T = 0$	$T = 70$	$T = 0$

Figure 6.4: SUBHIGH treatment parameters

In the SUGGEST treatment — the case of targeting policy — the subsidy is absent in all blocks, but in block 2 it is suggested by the experimenter to send not less then 70, so $T = 70$ (like in SUBHIGH treatment). See Figure 6.5.

Block 1	Block 2	Block 3
$E = 100$	$E = 100$	$E = 100$
$m = 3$	$m = 3$	$m = 3$
$Z = 0$	$Z = 0$	$Z = 0$
$T = 0$	$T = 70$	$T = 0$

Figure 6.5: SUGGEST treatment parameters

In the CONTROL treatment, the standard trust game, without any subsidies or suggestions, is played for all three blocks. See Figure 6.6.

Block 1	Block 2	Block 3
$E = 100$	$E = 100$	$E = 100$
$m = 3$	$m = 3$	$m = 3$
$Z = 0$	$Z = 0$	$Z = 0$
$T = 0$	$T = 0$	$T = 0$

Figure 6.6: CONTROL treatment parameters

We run all four treatments within the same session to control for the session specific effects. Subjects are randomly assigned to the treatment and to the role of the trustor or trustee. They keep their role throughout the whole experiment and are randomly matched with the other players from the same treatment in each period of the experiment (stranger matching design).[7] We keep the roles constant and use stranger matching since this design represents in our view a situation of repeated but independent decisions of the university to engage in spinoff activities.

The subjects privately receive payments at the end of the experiment according to the points they gained in one randomly selected period of the game.[8] Points are converted to Euros at the rate of 10 points for €0.35. Including a participation fee of €2.50, the subjects earned on average €6.81 with minimum €2.5 and maximum €15.5.

Table 6.1 summarizes the descriptive data about the subjects and their perception of the experiment obtained through the questionnaire given at the end of each experimental session. We almost perfectly balanced the sample on gender across the experiment (ratio of female participants: 0.49) and across sessions (ratio of female participants per session: 0.47, 0.5, 0.5, 0.47, 0.47, 0.53, 0.5). Also, we covered a wide range of age groups from 18 to 48 though most of the participants are relatively young (median age: 23.5).

As concerns the complexity of the experiment, subjects report a fairly high understanding of instructions with average value of 4.14 on a scale from 1 to 5 and the task difficulty as low, with mean 2.27 on a scale from 1 to 10.

Table 6.1: Participants characteristics

Statistic	N	Mean	St. Dev.	Min	Max
Age	224	24.147	4.040	18	48
Share of Females	224	0.491	0.501	0	1
Exp. Interesting	224	2.536	1.249	1	5
Exp. Length	224	2.304	0.871	1	5
Exp. Understandable	224	4.143	1.174	1	5
Task difficulty	224	2.268	1.556	1	8

[7]Though the order of matching is random, it is identical in all four treatments within the same session. That allows us to reduce the potential effects resulting from the history of the interaction.

[8]We use this scheme to avoid the endowment effect. See Azrieli et al. (2012) for the analysis of incentive schemes in experiments.

6.5 Results

6.5.1 Descriptive Analysis of Trust and Trustworthiness

To assess subject's behavior, we first compare the average amount sent in each round across the treatments. Figure 6.7 plots the average amounts sent over the game. The average amount sent across all the treatments in block 1 is similar to what other studies find[9] and equals to 40.24. From visual inspection, no evident difference in trust level shows up in block 1 across the four treatments. This is to be expected since subjects play the same standard trust game in all four treatments.

Now let's consider block 2. It is clear that subjects send more on average in the treatment SUGGEST than in any other treatment. This is especially evident if one compares the treatment SUGGEST (mean: 54.84) to CONTROL (mean: 40.22). One can also observe that the curve of the average amount sent in the treatment with suggestion is always above the similar curve for the treatments with subsidy. However, the plot does not show the difference between the amount sent in treatments with subsidy and the control treatment.

An interesting pattern emerges after the policy intervention. In block 3 the average amount sent in the SUGGEST treatment continues to exceed the corresponding value in the CONTROL treatment until the last periods of the game. On the contrary, the amount sent in the SUBHIGH treatment is lower than for CONTROL. The average sending in SUBLOW treatment is similar to the corresponding value in CONTROL treatment. To have a more clear picture of the difference between the treatments, we plot the cumulative distribution functions (CDF) for each of the three blocks (see Figure 6.8). The CDFs indicate the proportion of cases where the amount sent is smaller than a certain value, allowing us to have a detailed view of the distribution of the amount sent.

Again, we do not see any substantial difference between treatments in block

[9]See Johnson and Mislin (2011) for a meta–analysis of experiments based on the trust games.

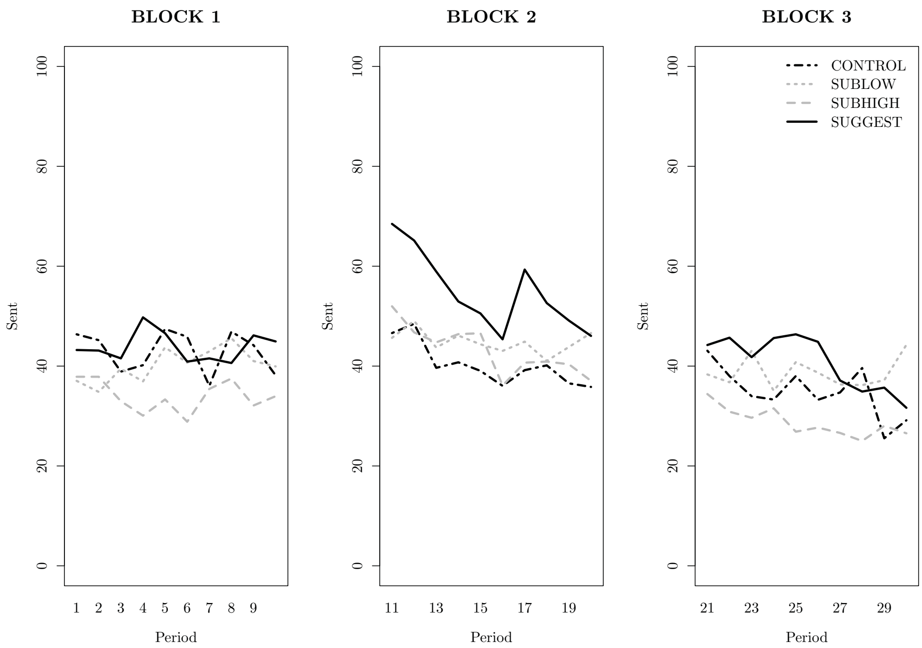

Figure 6.7: Average amount sent by treatment

1 but we observe a very different shape of the distributions in block 2. One can easily identify discontinuities in correspondence to the values of the low threshold ($T = 30$) for the treatment SUBLOW, the high threshold ($T = 70$) for the treatment SUBHIGH and the suggested amount to be sent ($T = 70$) for the treatment SUGGEST. Indeed, we observe changes related to the policy intervention.

Interestingly, we see very different distributions of the amount sent for the SUBHIGH and SUGGEST treatments if we look at the values that exceed 70 (the high threshold level or the suggested amount to send). While in the SUGGEST treatment subjects do not simply send the minimal level suggested, but continue to send higher values as well, in the SUBHIGH treatment almost no one provide contributions that are higher than that required for the subsidy. This pattern can be potentially explained by a crowding out effect and we will discuss it in more details in section 6.5.4.

As concerns block 3, one can observe that the curve of the cumulative distribution function for SUBHIGH treatment lies below the one of the CON-

TROL treatment and, on the contrary, the curve for SUGGEST treatment is above the one of CONTROL treatment.

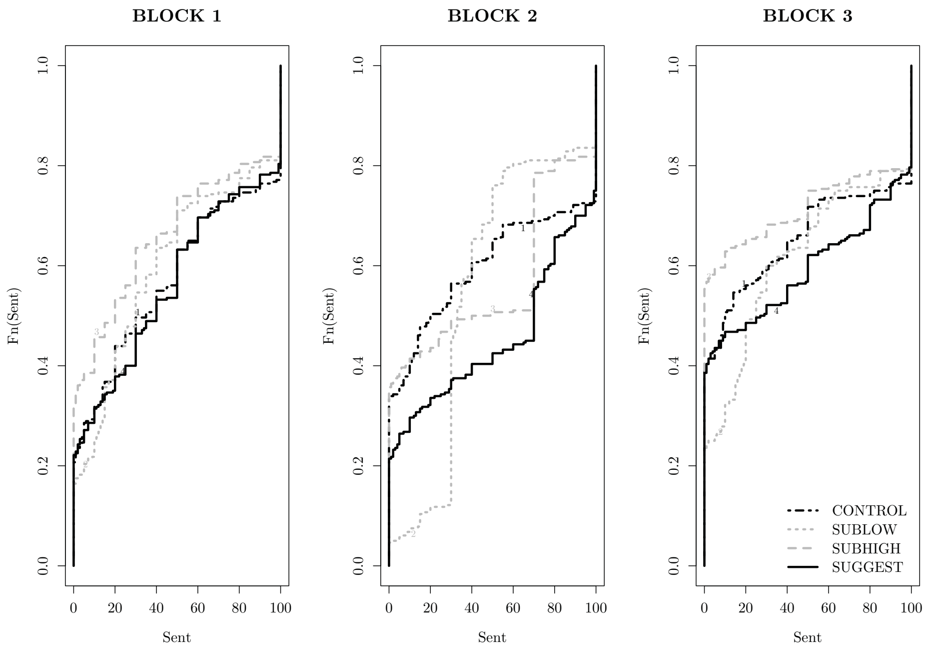

Figure 6.8: Cumulative distribution of amount sent by treatment

We conclude the descriptive analysis by discussing how much player 2 (trustee) sends back. To control for the fact that the amount the subjects can send back depends on the amount received, we calculate the ratio between the amount sent back by player 2 and the amount received by the same player — the trustworthiness rate, $r = \frac{R}{3 \cdot s}$. As expected, we do not observe any difference in trustworthiness between treatments (see Figure 6.9). The stability of trustworthiness across the treatments makes it possible to focus on the aim of our study, the analysis of the effects of external interventions on trust.

6.5.2 Regression Analysis of Trust and Trustworthiness

To assess significance of our results, we provide a regression analysis using a mixed effects model. We estimate the difference in amount sent, in the

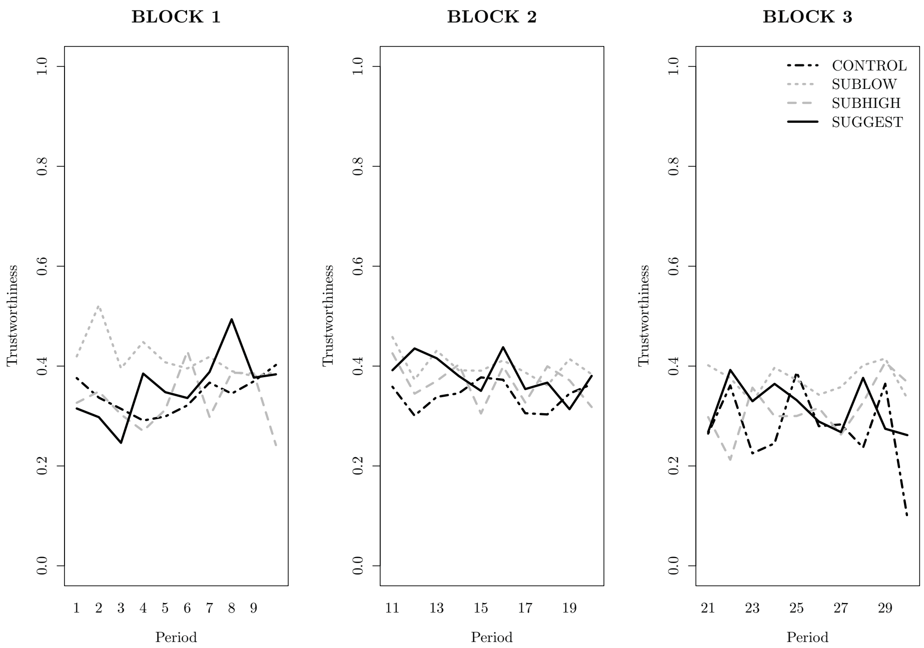

Figure 6.9: Average trustworthiness by treatment

trust level across treatments by running the following regression:

$$s = \beta_0 + \beta_{SG} SUGGEST + \beta_{SL} SUBLOW + \beta_{SH} SUBHIGH + \upsilon_i + \epsilon_{i,t}, \tag{6.11}$$

where $SUGGEST$, $SUBLOW$, $SUBHIGH$ are dummy variables that are equal to 1 for the corresponding treatments. υ_i is the random effect for subject i and $\epsilon_{i,t}$ is the error term for subject i in period t. The results are reported in Table 6.2.

In line with expectations and the observed pattern in Figure 6.7 we do not find a significant difference at any conventional level in the first ten periods. The behavior should not differ since there is no intervention in the first ten periods (block 1).

Now let's consider the effect of the intervention. We observe that subjects send significantly more in the SUGGEST treatment than in the CONTROL treatment during the first 5 periods of block 2 ($p = 0.064$; $\beta_{SG} = 16.3$).[10]

[10]Here and after the p–values for the linear models are obtained using the approximation

Table 6.2: Determinants of Sending by five periods — estimation of equation 6.11

	Sent (s)					
	Periods					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	1.2	0.6	16.3*	12.9	7.5	4.4
	(8.4)	(10.0)	(8.7)	(9.7)	(10.1)	(10.0)
SUBLOW	−5.2	−0.2	2.9	6.3	1.5	6.1
	(8.4)	(10.0)	(8.7)	(9.7)	(10.1)	(10.0)
SUBHIGH	−9.2	−8.7	4.4	1.5	−6.6	−5.7
	(8.4)	(10.0)	(8.7)	(9.7)	(10.1)	(10.0)
Constant	43.6***	42.2***	42.9***	37.5***	37.3***	32.5***
	(5.9)	(7.1)	(6.2)	(6.9)	(7.2)	(7.1)
Observations	560	560	560	560	560	560
Akaike Inf. Crit.	5,207.3	5,079.5	5,273.9	5,118.6	5,085.7	5,229.5
Bayesian Inf. Crit.	5,233.3	5,105.5	5,299.8	5,144.6	5,111.7	5,255.4

Note: *p<0.1; **p<0.05; ***p<0.01

During the next 5 periods of block 2 this difference remains positive, however, it is no longer significant ($p = 0.186$; $\beta_{SG} = 12.943$). Thus, we conclude that the targeting policy reaches its goal and positively affects the level of sending though only in the short–run.

As concerns subsidy–policy, its effect is less evident. We cannot reject the null–hypothesis that the average amount sent in the treatments with subsidies is the same as the average amount sent in the control treatment neither in the first five periods of block 2 (SUBHIGH: $p = 0.742$; $\beta_{SH} = 2.871$; SUBLOW: $p = 0.616$; $\beta_{SL} = 4.386$) nor for the next five periods (SUBHIGH:$p = 0.516$; $\beta_{SH} = 6.336$; SUBLOW:$p = 0.88$; $\beta_{SL} = 1.471$). Put it differently, we do not find an evidence that subsidy policy is an effective mean to promote trustful behavior in the short–run.

In the last ten periods of the game we do not find any significant post–intervention effects. The amount sent in the control treatment does not significantly differ from the one in any other treatment.[11] We observe, however, that the coefficient associated with the dummy for SUGGEST treatment is positive and larger than in the first periods of the game. This result sug-

of Kenward and Roger (1997).

[11] We as well do not find any significant difference comparing each of the treatments to each other.

gests that there can be a long-lasting effect of the targeting policy, though a further investigation is necessary.

We conclude this section by analyzing the evolution of trustworthiness r. Similarly to (6.11) we estimate the following regression:

$$r = \beta_0 + \beta^r_{SG} SUGGEST + \beta^r_{SL} SUBLOW + \beta^r_{SH} SUBHIGH + s + v_i + \epsilon_{i,t}, \tag{6.12}$$

In line with the theoretical predictions we do not find a significant difference over the entire experiment in trustworthiness rate between CONTROL, SUBHIGH, and SUGGEST treatments (see Table 6.7 in appendix 6.7.2). Trustworthiness is significantly different during the first five periods ($p = 0.047$; $\beta^r_{SL} = 0.11$) and the last five periods of the game for the SUBLOW treatment ($p = 0.071$; $\beta^r_{SL} = 0.124$). This difference might be driven by subjects idiosyncratic characteristics. To avoid interpretation of potentially biased results in the SUBLOW treatment we focus on the CONTROL, SUBHIGH and SUGGEST treatments, though we report the analysis of subjects behavior in SUBLOW treatment as well.

It is especially interesting to see no difference in trustworthiness between the treatments with subsidy and control during the intervention period: The subjects that are exposed to subsidy still do not significantly change their behavior. It indirectly points out that unconditional subsidy does not produce crowding out effect.

6.5.3 Net Payoff

Now, we consider how the reaction on different policies is reflected in the variation of payoffs. Specifically, we evaluate the effect of each policy on the average net payoff π_N, that is, the difference between the subject's payoff and the value of the subsidy (s)he gets: $\pi_N = \pi - Z$. We subtract the value of a subsidy to account for the costs of the third party. The following mixed–effect model is estimated:

$$\pi_N = \beta_0 + \beta^{\pi}_{SG} SUGGEST + \beta^{\pi}_{SL} SUBLOW + \beta^{\pi}_{SH} SUBHIGH + P + \upsilon_i + \epsilon_{i,t}, \tag{6.13}$$

where $SUGGEST$, $SUBLOW$, $SUBHIGH$ are dummy variables that are equal to 1 for the corresponding treatments. P is a dummy variable that is equal to 1 if the player is a trustor and 0 if the player is a trustee. υ_i is the random effect for subject i and $\epsilon_{i,t}$ is the error term for subject i in period t.

Table 6.3: Determinants of Net Payoff (π_N) by five periods – estimation of equation 6.13

	Dependent variable:					
	Net Payoff (π_N)					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	1.2	0.6	16.3**	12.9*	7.5	4.4
	(6.7)	(6.9)	(8.1)	(7.7)	(8.3)	(8.2)
SUBHIGH	−5.2	−0.2	2.9	6.3	1.5	6.1
	(6.7)	(6.9)	(8.1)	(7.7)	(8.3)	(8.2)
SUBLOW	−9.2	−8.7	4.4	1.5	−6.6	−5.7
	(6.7)	(6.9)	(8.1)	(7.7)	(8.3)	(8.2)
Player (P)	−67.8***	−59.3***	−76.9***	−67.9***	−69.3***	−65.9***
	(4.7)	(4.9)	(5.8)	(5.4)	(5.9)	(5.8)
Constant	177.5***	171.9***	181.3***	171.5***	171.9***	165.4***
	(5.3)	(5.4)	(6.4)	(6.1)	(6.6)	(6.5)
Observations	1,120	1,120	1,120	1,120	1,120	1,120
Akaike Inf. Crit.	12,329.4	12,493.2	12,459.2	12,474.6	12,581.9	12,671.8
Bayesian Inf. Crit.	12,364.6	12,528.4	12,494.3	12,509.7	12,617.0	12,707.0
Note:						*p<0.1; **p<0.05; ***p<0.01

As expected we find a significant increase in net payoffs during the first five periods of targeting policy ($p = 0.046; \beta^{\pi}_{SG} = 16.3$) as well as during the next five ($p = 0.092$; $\beta^{\pi}_{SG} = 12.943$). On the contrary, we still do not find significant effect of subsidy policy: The subsidy policy is ineffective both during the first five periods of intervention (SUBHIGH: $p = 0.59$; $\beta^{\pi}_{SH} = 4.386$; SUBLOW: $p = 0.724$; $\beta^{\pi}_{SL} = 2.871$) and during the next five (SUBHIGH: $p = 0.848$; $\beta^{\pi}_{SH} = 1.471$; SUBLOW: $p = 0.409$; $\beta^{\pi}_{SL} = 6.336$). To shed light on the reasons of these results, we provide further analysis in the next subsection.

6.5.4 Crowding–out

We wish to understand the potential cause of inefficiency of subsidy policy. To do that we focus on the distribution of the amount sent in treatments with different policy but with identical threshold level: SUBHIGH and SUGGEST.

At first we look at the subject's general propensity to follow the subsidy and the targeting policy. We compare the probability that subjects send an amount that is greater or equal to 70 in the SUBHIGH and SUGGEST treatments as opposed to CONTROL treatment. We do this by estimating the following regression:

$$Pr(s \geq 70) = \mathcal{L}(\beta_0 + \beta^{\geq}_{SG} SUGGEST + \beta^{\geq}_{SH} SUBHIGH + \upsilon_i), \quad (6.14)$$

where $\mathcal{L}$ is a standard logistic function. The results are reported in Table 6.4.

Table 6.4: Determinants $Pr(s \geq 70)$ by five periods – estimation of equation 6.14

	$Pr(s \geq 70)$					
	Periods					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	0.8	−0.02	3.0**	5.4**	0.8	0.1
	(1.6)	(1.7)	(1.2)	(2.3)	(1.8)	(1.6)
SUBHIGH	−0.2	−0.6	2.1*	4.2**	−0.4	−0.4
	(1.5)	(1.8)	(1.1)	(2.0)	(1.8)	(1.6)
Constant	−6.0***	−8.4***	−1.9**	−5.3***	−8.6***	−7.7***
	(2.0)	(1.5)	(0.8)	(1.6)	(1.5)	(1.5)
Observations	420	420	420	420	420	420
Akaike Inf. Crit.	338.9	266.9	399.4	329.1	274.3	285.8
Bayesian Inf. Crit.	355.1	283.1	415.6	345.3	290.5	301.9

Note: *p<0.1; **p<0.05; ***p<0.01

Of course, we find a significant increase in propensity to follow the targeting policy for the first five ($p = 0.0118; \beta^{\geq}_{SG} = 3.02; e^{\beta^{\geq}_{SG}} = 20.56$) as well as for the next five periods of block 2 ($p = 0.0167; \beta^{\geq}_{SG} = 5.4; e^{\beta^{\geq}_{SG}} = 222.45$). It is, however, more surprising to observe that subjects are significantly more likely to send the required amount during the subsidy policy as well (for periods 10–15: $p = 0.0632; \beta^{\geq}_{SH} = 2.09; e^{\beta^{\geq}_{SH}} = 8.04$; for periods 16–20:

$p = 0.0402; \beta^{\geq}_{SH} = 4.2; e^{\beta^{\geq}_{SH}} = 67$).

This result is puzzling since we do not observe that subjects send significantly more on average in the SUBHIGH than in the CONTROL treatment in block 2 (see Table 6.2 in section 6.5.2).[12] We can partially explain it by the fact that subjects' propensity to follow the policy tends to be lower in case of the SUBHIGH than in the SUGGEST treatment (for periods 10–15: $\beta^{\geq}_{SH} = 2.09 < \beta^{\geq}_{SG} = 3.02$; for periods 16–20: $\beta^{\geq}_{SH} = 4.2 < \beta^{\geq}_{SG} = 5.4$). Thus, given the sample size, we may not capture the effect directly.

The observed pattern points out that subsidy policy significantly affects the subjects' behavior but it is not that effective as the targeting policy because subjects avoid to follow the subsidy policy. This explanation can be partially accepted, however, one needs to compare whether the propensity to follow the policy is, indeed, significantly lower in case of subsidy than in case of suggestion. To do that we estimate the following regression using the SUBHIGH treatment as a reference category:

$$Pr(s \geq 70) = \mathcal{L}(\beta_0 + \beta^{\geq}_{SG} SUGGEST + v_i) \tag{6.15}$$

Nonetheless we do not find a significant difference in propensity to follow the policy between the SUGGEST and SUBHIGH treatments neither in the first five periods ($p = 0.3963; \beta^{\geq}_{SG} = 0.89; e^{\beta^{\geq}_{SG}} = 2.43$) nor in the next five periods of block 2 ($p = 0.6082; \beta^{\geq}_{SG} = 0.73; e^{\beta^{\geq}_{SG}} = 2.08$). The results are reported in Table 6.8 in Appendix 6.7.2. It suggests that another source of inefficiency is possibly at work and to find it we have a closer look at the distributions of the sendings in the SUBHIGH and SUGGEST treatments.

We have mentioned in Section 6.5.1 that the distribution of the sendings is different for the SUBHIGH and SUGGEST treatments in block 2. Subjects tend to send not more than the minimal amount 70 required to get the subsidy in the SUBHIGH treatment, while in the SUGGEST treatment the subjects also send more than the minimal level suggested (see Figure 6.8). If this difference is significant it explains why the effect of the subsidy policy

[12] As well as given that we do not observe significant growth in net payoffs during the subsidy policy (see Table 6.3 in section 6.5.3).

is not as large as the effect of the targeting policy.

To assess the significance of the observed disparity we evaluate whether the probabilities to send an amount that is greater than 70 or equal to 70 are different between the SUBHIGH and SUGGEST treatments. We estimate the following two logistic regressions using the SUBHIGH treatment as a reference category:

$$Pr(s = 70) = \mathcal{L}(\beta_0 + \beta_{SG}^{=} SUGGEST + v_i) \tag{6.16}$$

$$Pr(s > 70) = \mathcal{L}(\beta_0 + \beta_{SG}^{>} SUGGEST + v_i) \tag{6.17}$$

We report the results in the Tables 6.5 and 6.6. One can see that the probability of sending exactly 70 is significantly lower in the SUGGEST treatment as compared to the SUBHIGH treatment during the first five periods of block 2 ($p = 0.0234; \beta_{SG}^{=} = -1.71; e^{\beta_{SG}^{=}} = 0.18$). On the contrary, the probability of sending more than 70 is significantly higher in the SUGGEST treatment (than in the SUBHIGH treatment) also during the first five periods of block 2 ($p = 0.0254; \beta_{SG}^{>} = 3.44; e^{\beta_{SG}^{>}} = 31.29$).

Moreover, applying the non–parametric exact paired Wilcoxon test across aggregated averages over the sessions, we reject the null-hypothesis that there is no difference between the SUGGEST and SUBHIGH treatments in probability to send exactly 70 ($p = 0.0076$) and more than 70 ($p = 0.046$) during the first five periods of block 2.[13]

That is, in the SUGGEST treatment subjects tend to send more than 70 and, hence, contribute to the growth of the average amount sent. However, in the SUBHIGH treatment subjects tend to fulfill the requirement to get the subsidy but not to send more, diminishing the average level of contribution. Thus, the specific reaction on the subsidy policy decreases its effectiveness.

[13]We estimate the exact paired Wilcoxon test based on the Shift Algorithm by Streitberg and Röhmel (1986).

Table 6.5: Determinants of $Pr(s = 70)$ by five periods – estimation of equation 6.16

	$Pr(s = 70)$					
	Periods					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	1.1	0.7	-1.7^{**}	-1.7	-0.7	-0.51
	(1.2)	(1.2)	(0.8)	(1.6)	(1.2)	(2.2)
Constant	-4.9^{***}	-4.9^{***}	-1.6^{***}	-5.3^{**}	-4.2^{***}	-11.6^{***}
	(1.0)	(1.0)	(0.5)	(2.6)	(0.7)	(3.5)
Observations	280	280	280	280	280	280
Akaike Inf. Crit.	46.9	38.8	234.8	186.3	38.8	27.6
Bayesian Inf. Crit.	57.8	49.7	245.7	197.2	49.7	38.5
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 6.6: Determinants of $Pr(s > 70)$, in block 2 – estimation of equation 6.17

	Dependent variable:					
	$Pr(s > 70)$					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	0.7	0.4	3.4^{**}	2.0	1.2	0.7
	(1.1)	(1.9)	(1.5)	(2.0)	(1.8)	(1.7)
Constant	-3.2^{***}	-9.3^{***}	-3.7^{***}	-8.5^{***}	-8.8^{***}	-8.8^{***}
	(1.1)	(1.7)	(1.3)	(1.8)	(1.7)	(1.6)
Observations	280	280	280	280	280	280
Akaike Inf. Crit.	243.1	158.7	241.1	193.9	187.7	177.5
Bayesian Inf. Crit.	254.0	169.6	252.0	204.8	198.6	188.4
Note:						*p<0.1; **p<0.05; ***p<0.01

6.6 Discussion and Conclusion

In this section, we assess our contribution to the literature. We highlight the main results and provide a short discussion of the efficiency of the studied external interventions and the mechanisms acting behind them.

Our analysis falls under the broad rubric of studies on incentives and social preferences. It combines an exercise in decomposition of preferences to uncover sources of crowding–out with an attempt to account for the long-run detrimental effects of incentives.

We develop a model that predicts that the policy that involves monetary incentives can be ineffective since this type of incentives crowd-out other regarding preferences if subjects comply with the policy. We assume that preferences are endogenous (Bowles, 1998) — the preference once learned stays unchanged for some time. Therefore, the monetary–based policy that eradicates social preferences negatively affects the subjects' pro–social behavior after the intervention. On the contrary, the policy that uses non-monetary incentives is effective in the short-run and does not have detrimental consequences in the long-run because it does not influence other regarding preferences.

The experimental results, indeed, show that the non–monetary incentives are an effective tool to foster pro-social behavior, namely, trustful behavior in the short–run, while there is no evidence of detrimental effects of this type of incentives in the long-run. In turn, monetary incentives do not show their effectiveness in the short– as well as in the long–run though the policy significantly affects the subjects' behavior during the intervention. To interpret this fact we turn to the taxonomy of incentive effects on preferences provided by Bowles and Polania-Reyes (2012).

According to their taxonomy, there are three mechanisms linking interventions and preferences: 'bad news' — incentives provide information about interests of a principal; 'control aversion' — incentives jeopardize self determination; 'moral disengagement' — incentives activate a switch from pro–social to own payoff maximization mode of thought. We do not consider here the first one ('bad news') since the incentives are provided by the third–party and, hence, should not affect the subjects' behavior. However, the last two — 'control aversion' and 'moral disengagement' — can explain the specific pattern of subjects reaction on the subsidy policy.

Subjects react to the monetary policy but i) their propensity to follow this policy is low and ii) those who follow the policy send the minimal amount required to get the subsidy. We attribute the low propensity to follow the policy to the mechanism of 'control aversion': Subjects perceive the policy as controlling and avoid following it. The 'moral disengagement' can explain the fact that subjects send mostly the minimal amount: They switch their way of thinking to own–payoff maximization, thence, if they decide to follow the policy they simply minimize their costs by sending the minimal amount.

As concerns the post–intervention effect of the policies, despite the fact that we do not find a significant difference between treatments after policy interventions, we observe that subjects tend to send a high amount after the targeting policy. This is an interesting observation since it suggests that a targeting policy can have a potential long–lasting effect. Nevertheless, further research is needed to test this observation.

It is also interesting to observe that the trustworthiness rate is not affected during the intervention as well as it does not change afterwards. On the one hand, this goes in line with theoretical expectations — the trustee's behavior should remain the same since the policies incentivize only trustors. On the other hand, given that trustees also receive subsidies, this fact suggests that the presence of a subsidy is insufficient to crowd out other-regarding preferences. It is rather likely that the crowding–out occurs when the monetary incentives are conditioned on a certain behavior.

To sum up and conclude, in this study, we aim to understand how subsidy and targeting policies affect an investment decision. We employ a multi–period trust (investment) game where we introduce an external intervention either in form of subsidy or suggestion and analyze the level of trustful behavior during and after the intervention.

We find that targeting is an effective instrument to promote trustful behavior whereas subsidy policy is not effective both in the short– and long–run: Subjects follow the targeting policy and send even more then minimal level requested, while under the subsidy policy they exhibit low propensity to follow the policy and send mostly the minimal amount needed to get the subsidy. We therefore recommend the targeting policy as one of the instruments to foster trustful behavior.

6.7 Appendix

6.7.1 Instructions

Player 1, Trustor

Welcome to the experiment!

Thank you very much for participating. We hope that you feel comfortable. We ask you to remain quiet and do not communicate with any other player. Please understand that in case you communicate with other players we will have to exclude you from the experiment without payment. If you have any questions please raise your hand and wait for the experimenter to come to you.

We guarantee that all information collected during the experiment undergoes a strict anonymity process. It ensures anonymity among players and that you stay anonymous to the experimenter.

During the experiment you will see information about other players. We have ensured that you cannot identify them personally as well as they cannot identify you.

The experiment is on decision-making. Your earnings will depend partly on your decisions and partly on the decisions of other players. You will have to make one decision in each round of a simple game which consists of 30 rounds.

In each round of the game the earnings will be calculated in points. At the end of the experiment **one round** will be randomly chosen. The points gained during this round will be converted to Euros with the following rate:

$$10 \text{ points} = 0.35 \text{ Euro}$$

In addition, you will receive 2.50 euro as a compensation for showing up on time. The game you will play is divided **into three blocks** (A, B and C), with 10 rounds in each block.

In each round of any block you will be matched with another randomly chosen player among other participants. There will be a new random pair each round.

The information about your previous decisions will not be revealed to other players at any round of the experiment.

In each round you and the other player both will be endowed with 100 points. **You can send any amount** to the other player. **Each point you send is tripled.** The other player will decide how many points to send back to you and how many points to keep (from zero to the tripled sum you sent).

[For the SUBHIGH and SUBLOW treatment we add the following paragraph]

Also, in some blocks if you send **not less than a certain minimum**, you and the other player will receive **an additional payment**. The amount of the **additional payment** and the required minimum sent to receive it will be specified in the beginning of each block.

[For the SUGGEST treatment we add the following paragraph]

In some blocks it will be suggested to send not less than a certain amount. The amount suggested is specified at the beginning of each block.

Player 2, Trustee

Welcome to the experiment!

Thank you very much for participating. We hope that you feel comfortable. We ask you to remain quiet and do not communicate with any other player. Please understand that in case you communicate with other players we will have to exclude you from the experiment without payment. If you have any questions please raise your hand and wait for the experimenter to come to you.

We guarantee that all information collected during the experiment undergoes a strict anonymity process. It ensures anonymity among players and that you stay anonymous to the experimenter.

During the experiment you will see information about other players. We have ensured that you cannot identify them personally as well as they cannot identify you.

The experiment is on decision-making. Your earnings will depend partly on your decisions and partly on the decisions of other players. You will have to make one decision in each round of a simple game which consists of 30 rounds.

In each round of the game the earnings will be calculated in points. At the end of the experiment **one round** will be randomly chosen. The points gained during this round will be converted to Euros with the following rate:

$$10 \text{ points} = 0.35 \text{ Euro}$$

In addition, you will receive 2.50 euro as a compensation for showing up on time. The game you will play is divided **into three blocks** (A, B and C), with 10 rounds in each block.

In each round of any block you will be matched with another randomly chosen player among other participants. There will be a new random pair each round.

The information about your previous decisions will not be revealed to other players at any round of the experiment.

In each round you and the other player both will be endowed with 100 points. You will receive some amount of points from the other player. **Each point sent by the other player is tripled. You can decide** how many points to send back to him and how many points to keep (from zero to the tripled sum of points the other player sent).

[For the SUBHIGH and SUBLOW treatment we add the following paragraph.]

Also, in some blocks if the other player sends **not less than a certain minimum**, you and the other player will receive **an additional payment**. The amount of **the additional payment** and the required minimum sent to receive it will be specified in the beginning of each block.

[For the SUGGEST treatment we add the following paragraph]

In some blocks, it will be suggested to other player to send not less than a certain amount. The amount suggested is specified at the beginning of each block.

6.7.2 Additional Estimations

Trustworthiness

Table 6.7: Determinants of trustworthiness by five periods – estimation of equation 6.12

	Trustworthiness (r)					
	Periods					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	−0.004	0.1	0.04	0.04	0.1	0.1
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
SUBLOW	0.1^{**}	0.05	0.1	0.1	0.1	0.1^{*}
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
SUBHIGH	−0.01	0.01	0.03	0.04	0.02	0.1
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Sent (s)	0.002^{***}	0.002^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.3^{***}	0.3^{***}	0.3^{***}	0.2^{***}	0.2^{***}	0.2^{***}
	(0.04)	(0.05)	(0.1)	(0.1)	(0.05)	(0.1)
Observations	459	405	455	398	371	312
Log Likelihood	57.4	51.6	102.8	94.6	64.1	31.6
Akaike Inf. Crit.	−100.7	−89.1	−191.7	−175.2	−114.3	−49.1
Bayesian Inf. Crit.	−71.8	−61.1	−162.8	−147.3	−86.9	−22.9

Note: *p<0.1; **p<0.05; ***p<0.01

Probability to Follow the Policy (SUGGEST VS. SUBHIGH)

Table 6.8: Determinants $Pr(s \geq 70)$ by five periods – estimation of equation 6.15

	$Pr(s \geq 70)$					
	Periods					
	1-5	5-10	11-15	16-20	21-25	26-30
SUGGEST	0.8	0.6	0.9	0.7	1.2	0.5
	(1.1)	(1.8)	(1.0)	(1.4)	(1.8)	(1.7)
Constant	-3.3^{***}	-9.0^{***}	0.2	-0.7	-9.1^{***}	-8.6^{***}
	(1.1)	(1.7)	(0.7)	(1.0)	(1.7)	(1.6)
Observations	280	280	280	280	280	280
Akaike Inf. Crit.	248.9	172.1	280.0	250.6	185.4	180.9
Bayesian Inf. Crit.	259.8	183.0	290.9	261.5	196.3	191.8
Note:						*p<0.1; **p<0.05; ***p<0.01

Chapter 7

Conclusion

"*(The plants and animals of the Galapagos differ radically among islands that have) the same geological nature, the same height, climate, etc (...). This long appeared to me a great difficulty, but it arises in chief part from the deeply seated error of considering the physical conditions of a country as the most important for its inhabitants; whereas it cannot, I think, be disputed that the nature of the other inhabitants, with which each has to compete, is at least as important, and generally a far more important element of success.*"

— Charles Darwin, cited in Hoff (2000)

7.1 General Remarks

This Doctoral Thesis hopes to be a sort of 'Voyage of the Beagle' through the factors that shape the making of some peculiar 'irregularities' of the world of technological change. The port of departure for this voyage has been a questioning of the common understanding of General Purpose Technologies, aimed at both redirecting and extending their theoretical reach. In the open sea (of knowledge), the chosen course to investigate those irregularities has been that to focus the analysis on the nature of — and interaction between — the many (economic and technological) domains involved in determining a technology pervasiveness. A search for GPTs has hence turned into an exploration of linked markets.

As Darwin's voyage lasted much more than initially programmed, also the voyage contained in this Thesis touched conceptual locations placed beyond the narrow domain of GPTs. The strength and direction of competitive selection when markets are integrated in value chains, and the purposeful intervention to foster the commercialization of academic knowledge through the creation of spinoff ventures, all represent network phenomena in which incentives, constraints, and payoffs are not independent of what happens in linked contexts.

Taking stock, the claim of the Thesis is that the multilevel dimension of market interactions should be (or should return, depending on the history of economic thought and reference community favoured by the reader) at the core of economic analysis, because it is looking at non–trivial feedbacks and cascades of effects that unexpected results may be found. The theory of GPTs, and a more general account of economic and technological dynamics in linked markets, appear from this perspective as pieces in the bigger jigsaw puzzle of economic evolution, where the economy is a complex system moving on the tracks of techno–economic paradigms and technological trajectories.

As a conclusion serves to summarize the successes and failures of any enterprise, in what follows the main findings and the novelty of the Thesis are highlighted. Also, the possible implications for policy that can be derived from the studies contained in the Thesis are emphasized, and the limitations and some ways ahead for the research perspective developed in the previous pages are indicated.

7.2 Main Findings

In Chapters 2, 3 and 4 the Thesis suggests a viable path to extend the economic approach to GPTs, that i) incorporates theoretical building blocks from related strands of literature, ii) repositions the study of pervasive technological change within the realm of phenomena of interest for Industrial Dynamics, and iii) offers a simple framework to understand the factors determining potential GPTs' success or the failure to become pervasive and prevalent.

The general findings can be summarized recalling the three statements that, at the end of each section of Chapter 3, describe the step–by–step transition from the theory of GPTs to a theory of technological multipliers:

1. GPTs, meant as a networked phenomenon, can be considered a special case of spillovers, namely inter–industry (vertical) spillovers involving enabling technologies and technological complementarity;
2. in its dynamics, a GPT cluster is a special case of unbalanced development, with a peculiar structure of interaction, and focused on cascades of effects on innovative activities rather than economic performance. The enabling nature of technological complementarities and spillovers, the feedbacks taking place within the GPT cluster, and the heterogeneous distribution of responses to these inducement effects can result in a synchronous or in an asynchronous change;
3. an extended theory of GPTs and GPT clusters is in a more general way a theory of technological multipliers, in which an enabling technology affects the sectors to which it is linked, and it is affected by them. The net effect resulting from positive feedbacks, driven by economic and technological complementarity, and negative feedbacks, determines if the technology or the sector under consideration succeeds to gain pervasiveness, to establish a GPT cluster and eventually to influence the direction of an economy's evolution.

Additionally, the 'Ricardian' model of technological specialization described in Chapter 4 offers a set of insights regarding the outcomes of an upstream competition for a downstream market, where one (or more) potential new GPT–like technologies strive to acquire purposes. New upstream technologies can succeed in 'conquering' the whole downstream market, can fail and be confined in niches, or can share the downstream market with the established GPT on a rather equal standing. In general terms, the lesson to be taken home from Chapter 4 is that, in the context of linked markets, the array of scenarios that the process of purposes acquisition can produce is rather wide; economic agents can act on different 'levers' to influence the results of the competition for the (downstream) market.

In Chapter 5 the Thesis derives a set of theoretical results from the analytical and computational analysis of the replicator dynamics in value chains. The propositions outlined in the Chapter suggest that firms integrated into value chains do not necessarily increase (decrease) their market share even though they have a higher (lower) fitness than the reference population. The very existence of value chains relations may induce violations of the replicator dynamics, that we labeled 'regressive developments' of market selection. Additional results deal with the intensity, rather than with the direction, of market selection. In fact, the Chapter shows that, in the scenario with firms randomly matched and with the possibility to switch partners between value chains, competition generates high market shares volatility in every innovation and returns to scale setting. This result raises new questions about our understanding of market turbulence and industry life cycle patterns. Another finding of the Chapter has to do with the differential strength with which market selection shapes firms' success and failure across value chains layers; this opens room for the definition of a set of competition policies that are tailored for the particular market of intervention.

In Chapter 6 the Thesis offers both a theoretical model and an experimental analysis that explain the short– and long–run dynamics of a trust relationship between agents when an external intervention is introduced. More specifically, the agents are universities and academic spinoffs, and the study aims at capturing which type of interventions — a subsidy, or a targeting policy — is more effective, or less harmful in case the displacement of intrinsic motivations (crowding–out) occurs. Theoretically, the Chapter finds that the interaction of other–regarding preferences and compliance to authority are among the elements that can explain the better performance of targeting (suggestions) policies. Empirically, the main finding is that monetary incentives (subsidies) do not significantly increase investment levels, while the targeting policy in which authorities suggest a desired behavior increases the investment activity during the intervention and does not have long–run (post–intervention) detrimental effects. Experimental subjects tend not to follow the subsidy policy; if they do, they send mostly the lowest amount required to obtain the subsidy.

In sum, the findings of the Thesis range from conceptual contributions to a generalized and more consistent definition of GPTs and technological multipliers, to analytical contributions on how the vertical relation among markets affects outcomes such as technological pervasiveness (acquired purposes) and selection (replicator dynamics), and finally to an experimental contribution to the design of policies that can strengthen the trustful ties between Academia and Industry.

7.3 Novelty

The main novelty of the Thesis is the micro– and mesoeconomic approach to GPTs. This perspective suggests the possibility to study *GPTs as networked and complex phenomena*. The generalization of the modeling and empirical analysis of GPTs to a broader research agenda dedicated to the Microeconomics of heterogeneous technical change and linked markets is a first step towards a novel interpretation of the process of generic technological change.

The broader objective of the original theoretical analysis presented in the Thesis is to build a bridge between two distinct research traditions: a short term Economics of Innovation, and a long term study of Long Waves, techno–economic paradigms, and technological revolutions. Both the traditions encountered limitations: on the one hand, the microeconomic study of innovation is still short of contributions capable to model and identify the micro–to–macro causal channels connecting the ‘locus of learning’, meaning the firm, to the macroeconomic implications of restless creative destruction. On the other hand, the study of Long Waves is caught between the limited heuristic power of theories that are mainly historical in kind, and the difficulties to find the unbiased ‘filtering’ method to identify periodic cyclical patterns in the evolution of economies. The nature of Long Waves, divided between being just a consequences of Mankind’s pattern–seeking need, a statistical outcome at the edge of Chaos, or a phenomenon *caused* by innovation, is yet to be fully uncovered.

The novelty of the Thesis lies also in the fact that it provides the first attempt to generalize the replicator dynamics by incorporating in the model the vertical relations between markets linked in value chains. In a historical phase in which the functioning of the world economy revolves around the organization of production in global value chains, it is of utmost importance to understand if, and how, market selection takes place and if the competition for the market affects — and is affected by — the very existence of value chains linkages. Hence, a multilevel view of market dynamics is definitely a major novelty of the Thesis.

Finally, the Thesis provides a novel and fresh contribution to our understanding of the effects of given Science and Innovation policies. Both the methodology — an experimental study with an original design — and the research questions, that focus on the assessment of different policy schemes and their long–run (post–intervention) consequences, represent an original contribution to the literature.

7.4 Policy Implications

Concerning the policy dimension, the Thesis offers insights on several dimensions.

Firstly, concerning GPTs and technological competition in vertically–linked markets, a case is made for the evaluation of different policy mixes, meant as multiple levers capable to affect the 'jump' between different equilibria, that, in turn, are the possible outcomes of the competition between upstream technologies striving to acquire generality of purpose.

Secondly, for what regards market selection when value chain relations are taken into account, the implications for policy are mostly related to the fact that the 'survival of the fittest' principle acts with heterogeneous strengths across the layers of the value chains. This result supports the view that one–size–fits–all policies may fall short of effectiveness, given that they do not account for the variety of market dynamics.

Thirdly, regarding the study of external interventions and trust between universities and academic spinoffs, the relevant policy implication has to do with the choice of the appropriate schemes capable to foster, rather than hinder, knowledge commercialization. The Chapter suggests that non–monetary policies such as targeting ones may exploit authority–related mechanisms and produce better results during and after the period of intervention.

7.5 Limitations and Research Ahead

This Thesis is a contribution to the economic understanding of technological change, innovation, industry dynamics, market selection and knowledge commercialization when different levels of analysis are interdependent. The research effort was certainly not exempt from trade–offs. In the design of the Thesis, and during its progressive construction, alternative paths and logical chains of analysis have been pursued or left aside. Trade–offs, one of the essences of economic reasoning, apply to research as well. In this sense, the limitations of the Thesis are all those research routes that have not been yet crossed, the possible extensions not yet modeled, and the robustness checks not yet tested.

In particular, the empirical analysis of GPTs and technological multipliers has been introduced, but not fully developed. An exhaustive theory of technology–induced feedbacks requires also to provide a sound methodological framework in order to test for the empirical relevance of the theoretical insights developed in the Thesis.

Another limitation has to do with the lack of a more in–deep study of some of the phenomena touched upon in the Thesis. For example, a through extension of the Ricardian model of Chapter 4 — one incorporating also features taken from complex networks and percolation models — may shed some additional light on the unbalanced process of purposes acquisition. The same remark holds for the replicator dynamics in value chains, where a deeper exploration of the conditions under which regressive developments of market selection occur (and the role vertical relations plays in that) could offer further insights on the microeconomic dynamics underlying the heterogeneous strength of market shares reallocation across markets.

The limitations of the Thesis also help to draw the lines to identify some potential ways ahead for the study of linked markets. In fact, several paths to extend the studies proposed in the Thesis can be outlined. If innovations are 'like troubles', in the sense that they 'do not come singly, but in battalions' (Freeman, 2004, p. 550), the same holds for research questions.

A first extension has to do with the arguments developed in Chapter 3: combining input–output tables and innovation input (R&D) data, a set of indicators of upstream and downstream pervasiveness for industries or entire *filières* can be derived, and their dynamics tracked over time. In a sense, this approach would feature an empirical application of Industrial Dynamics methodologies and methods (for example, Markov transition matrices and mobility analysis could be used in this context) to the generalized and networked conceptualization of GPTs provided in the Thesis. The aim of this extension would be to measure the technological 'power of pull' of given industries, technologies, and *filières* in order to inform policy–makers of the magnitude and direction of technological multiplier effects.

A second extension goes in the direction of the analysis developed in Chapters 3 and 6, namely to identify or design the best policies for industrial technological upgrading. In this sense, the 'hirschmanian' perspective on the importance of bottlenecks and linkages to generate between–industries inducements could be pushed forward by exploring the effects of purposeful creation and removal of economic and technological bottlenecks. An extension along this lines may provide additional useful evidence on the stability and resilience of economic linkages, to be used in the setup of industrial policies at the regional, national and also supranational (for example, European) level. A specific set of research questions in this context could point at the effect of innovative public procurement when multiple potential GPTs compete for the downstream market and strive for pervasiveness, as suggested in Chapter 4 of the Thesis.

A Third extension builds on the contribution of Chapter 5 on market selection. Exceptions to the expected behavior of the replicator dynamics can depend on the structure of value chains, but also on other factors that are well–known in Economics of Innovation; for example, policy interventions, and cooperations among firms. In a nutshell, the theory of market selection can incorporate further dimensions of analysis in order to become a more general theory of *market interactions*.

Eventually, a fourth extension looks at the modeling side, and refers to the contribution of Chapter 4. Firstly, the model of vertically–related markets can be extended to take into account the patterns of within–markets firms behaviors in term of entry and exit. A way forward in this sense is to establish a connection between models of Industry Life Cycles and models featuring linked markets, in order to begin an investigation of multilevel Industrial Dynamics. Secondly, a theoretical contribution aimed at extending our understanding of technological change and linked markets could build a bridge with the literature on platforms, two– and multi–sided markets, given that also in this literature the general phenomenon under scrutiny has to do with the incentives and constraints shaping the dynamics of 'star economies'. In this case, the focus would be on the dynamic determination of market structures at different, linked levels. Indeed, to combine the building blocks of multi–sided markets and GPTs (and also those of the most recent contributions on dynamic oligopoly theory) could represent a step ahead towards a study of interdependent market structures.

To conclude, this Doctoral Thesis has highlighted the potential generality of an economic analysis of markets that are linked by technological and economic ties. It is a partial account of an object of analysis that is indeed relevant, but also very broad. However, to the author this partial account seems to be on the right track for what concerns the direction to be followed in order to better understand the evolution of markets and societies. In fact, we share the remark of Lord Keynes: it is better to be partially right, than completely wrong.

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